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DISCUSSION PAPER SERIES

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ABSTRACT

Field of Study and Mental Health in Adulthood*

We analyze whether field of study assigned at age 16 impacts mental health in adulthood. Using a regression discontinuity design that exploits GPA cut-offs, we find that admission to the preferred study field improves mental health, lowering both the incidence of antidepressant prescriptions and of mental health-related hospitalizations. Engineering contributes strongly but not uniquely to the positive results. As for mechanisms, earnings explain 40% of the estimates, but earlier proposed hypotheses based on school-age peer characteristics have little explanatory power. Our findings imply that restrictions on individuals' choices, to improve human capital allocations, entail costs that may have been underestimated.

JEL Classification: I10, I21, I24, J24, J28, J32

Keywords: field of study, health, secondary education

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1. Introduction

The global burden of disease attributable to mental health disorders has been rising constantly and is now the second leading cause of years lived with disability globally (IHME, 2020).[1] More than 50% of all individuals are expected to be diagnosed with a mental illness at some point during their lifetime (Kessler et al. 2007). Among the mental illnesses, the most prevalent are depressive disorders and anxiety disorders. The World Health Organization (WHO) estimates that at any given time, 6 to 8% of the world's population suffers from depression or anxiety (James et al. 2018), presumably decreasing individuals' productivity and overall wellbeing as well as societal welfare. In Sweden (the setting of this paper), the National Board of Health and Welfare estimates that depression and anxiety, together with adaptation difficulties, account for approximately 40% of all sick leave taken by the working population (Socialstyrelsen, 2019).

As societies struggle to address this issue, economists have contributed insights about the causal relationship between socioeconomic factors and mental health. For example, studies have reported a positive causal impact on mental health of neighborhood quality (Kling et al. 2007), religiosity (Fruehwirth et al. 2019), a negative impact of poverty or worsening labor market conditions (Ridley et al. 2020, Pierce and Schott 2020), whereas the evidence for positive income shocks is mixed (Christian et al. 2019, Apouey and Clark 2015, Lindqvist et al. 2020, Cesarini et al. 2016).[2] Early-life circumstances have been found to be relevant (Adhvaryu et al. 2019), even

[1] Years lived with disability (YLD) represents the number of years of healthy life lost due to disability caused by the non-fatal experience of disease or injury in a population (see Kirch 2008). Mental disorders cause 14.6% of years lived with disability (1 in 6 years), second only to musculoskeletal disorders, which cause 17% of all years lived with disability, while all types of cancer cause 0.9%, and cardiovascular diseases 4%.

[2] Conflicting evidence about the role of income shocks come from lottery wins. Apouey and Clark (2015) show that lottery winners enjoy better mental health compared with those who win less or play but do not win, but other studies show that lottery winning has small to no impact on mental health when fully controlling for the number and frequency of lottery tickets bought (Cesarini et al. 2016, Lindqvist et al. 2020).

as early as in utero (Persson and Rossin-Slater 2018), but adolescence is regarded as a particularly important period for shaping adult mental health (Kessler et al. 2005, Ferguson et al. 2007). During adolescence, significant biological changes occur, and many individuals start to evaluate their own personal and social worth (Blakemore 2019). One very important decision taken during adolescence is the choice of field of study, which typically occurs at age 15 or 16 in most OECD countries, but due to data limitations its consequences on mental health are virtually unexplored.

In this paper, we examine the long-term causal impact of eligibility at age 16 to a preferred field of study on adult mental health. Among several arguments about why there could be such a relation, the most obvious ones are that the chosen field of study is linked both to the individual's career preferences and their comparative advantages. These factors may have long-term effects on mental health either directly through greater job satisfaction and/or indirectly via higher earnings. In addition, it is possible that the immediate disappointment of being denied access to the preferred field of study, at a sensitive age, may have effects on later mental health due to loss of motivation and self-esteem. Documented indications of path dependence in mental health, particularly for severe conditions such as major depressive disorders, would then increase the likelihood of long-term effects on mental health (Hardeveld et al. 2010, Buckman et al. 2018).[3]

We address, first, whether being admitted to the preferred field of study has an impact on adult mental health. Second, in a context where there is no clear ranking between the fields of study, we investigate to what extent admittance to an explicit field of study affects mental health in adulthood. This analysis provides more detailed information with estimates on adult mental health separated by different curricula, presumably also capturing the impact of different career

[3] It has also been argued that mental health is malleable before age 20, and persists into adulthood (e.g., Kiessling and Norris 2023).

paths and other circumstances specific to being admitted to a certain field of study. Our analyses are based on Swedish register data of all applicants to high school between 1977 and 1991, which include information on GPA, admission decisions and actual enrollment and completion of the field of study. Students are admitted to fields of study in the 10th grade, aged 16, based on their preference rankings over fields of study and ninth grade GPA. The framework creates sharp admission thresholds for different majors. This feature is exploited in a regression discontinuity design, as individuals with almost identical backgrounds exhibit large differences in the probability of completing their first-choice field of study. In addition, personal identifiers allow us to merge the data with indicators of mental health in the form of antidepressants prescribed between ages 40 and 45 and hospitalization due to mental disorders (anxiety, depression, drug abuse, sleeping or eating disorders) when aged between 36 and 44.

We find that being marginally admitted to a preferred field of study at age 16 yields a statistically significant lower probability of being prescribed antidepressant medication. These results are corroborated by estimates indicating that being marginally admitted to a preferred field of study also decreases the probability of being hospitalized due to mental disorders. The results thus indicate improvements, almost three decades later, both in terms of mild and medium mental disorders (fewer antidepressants), and improvements in terms of severe mental disorders (fewer hospitalizations). The findings suggest that restrictions on individuals' field of study choice, intended to improve the efficiency of human capital allocation, cause long-term costs that may have been underestimated. The estimates are mainly driven by students who were marginally admitted to Engineering and, to a lesser extent, Business majors. There is also less precise evidence that students marginally admitted to Humanities exhibit a significantly higher likelihood of being prescribed antidepressants but no statistically significant impact on hospitalization.

Our study is mainly related to two strands of the economics literature. The first is the relatively limited literature that investigates the causal effects of pursuing particular fields of study. [4] For high school field of study choice, Dahl et al. (2023) use a similar set-up compared with the present study and find high school majors to have substantial effects on earnings as measured by age 38, mediated primarily by differences in occupation. Their earnings estimates are generally positive for Engineering, Natural Science and Business but negative for Social Science and Humanities. Other studies have focused on college major choice and typically find very large effects on earnings (e.g., Kirkeboen et al., 2016, Bleemer and Mehta, 2022, Britton et al., 2022).

The second related strand of literature investigates the determinants of mental health.[5] The present paper contributes by connecting adult mental disorders with adolescence and schooling, and is in this sense most closely related to studies that have focused on the role of schooling or school environment in shaping mental health. However, the impact of additional schooling on mental health (examined with compulsory schooling reforms) has provided mixed results. Crespo et al. (2014) use data from several European countries and find that one extra year of school, decades later, decreases the likelihood of depression by 6.5 percentage points. This corresponds to 30% compared with the sample mean of 21.6%. In contrast, Dahmann and Schnitzlein (2019) find no evidence for a protective effect of education on mental health in West Germany. Their IV results cannot even rule out negative effects on mental health. Indeed, Courtin et al. (2019) find that increased school length in France leads to *higher* levels of depressive symptoms for women aged 45 or above, but no effects for men, and Avendano et al. (2017) find the 1972 extension of

[4] See Altonji et al. (2012, 2016) for excellent introductions to this literature.
[5] See references above to Kling et al. (2007), Apouey and Clark (2015), Cesarini et al. (2016), Fruehwirth et al. (2019), Christian et al. (2019), Ridley et al. (2020), Pierce and Schott (2020), Lindqvist et al. (2020).

compulsory schooling in the United Kingdom to increase the incidence of depression in adulthood for both men and women. Their interpretation is not that more schooling *per se* leads to worse mental health, but rather that forcing low-achieving students to remain in school may have long-term negative consequences for their mental health.[6]

Other studies have evaluated whether school quality or different aspects of peer composition affect mental health. Butikofer et al. (2023) investigate the short-term effects of the eligibility to enroll in a higher achieving high school in Norway and find that it increases the probability of enrollment in higher education and decreases the probability of diagnosis or treatment of psychological conditions during college. They find evidence to suggest that these effects are driven by the composition of peers and of teachers in the more selective schools. In a related vein, Kiessling and Norris (2023) find that the relative ability rank within the peer group has significant consequences on mental health at least 14 years later. Conditional on own ability, they report that one standard deviation increase in the students' relative ability rank leads to an improvement in their mental health by 6% of a standard deviation. This effect is driven by students who receive negative rather than positive shocks to their relative ranks. Getik and Meier (2022) instead examine the classroom peer gender composition and find that a higher share of female peers during compulsory schooling increases the incidence of mental health diagnoses, particularly among boys. Giulietti et al. (2022) report that, for women, the share of own-gender schoolmates who are depressed is linked with an increase in the probability of depression in adulthood. The result is mediated by a lower probability of college attendance, a lower probability of labor force participation, and consequently by a reduced income for the affected adult women.

[6] In the context of Zimbabwe, Kondirolli and Sunder (2022) report that further schooling decreases depression or anxiety symptoms more than two decades later, likely mediated through improved physical health. Also, Böckerman et al. (2021) investigate the effects of a reform in Finland, which delayed tracking from when pupils were aged 11 to 16. They find no overall effects on mental health-related hospitalizations.

The present study makes several contributions. First, we provide the first quasi-experimental estimates of the impact of gaining access to a preferred field of study on mental health in adulthood. Second, we estimate whether specific fields of study during high school affect mental health in adulthood. Although choosing a field of study at the beginning of high school is a salient feature in most countries' upper secondary school systems, there are no other studies, to our knowledge, that causally investigate the relationship between field of study and mental health in adulthood. Third, our study is informative about the mechanisms behind mental health disorders, and thereby complements the earlier literature. In this regard, we find suggestive evidence that about 40% of the effects from field of study choice on mental health can be attributed to differences in expected earnings. In contrast, we find no or limited support that the immediate disappointment of being denied access to the preferred field is an important mechanism, nor for previously proposed school environment indicators such as peer quality, individual GPA rank, female share or the length of schooling rather than the curriculum, and the same holds for adult age outcomes related to family formation, occupation or workplace. However, these last two findings are at odds with a large body of correlational evidence emphasizing the importance of job-characteristics for mental health. Using register data on occupation and workplace, we note that it is not possible to account for the quality of the match between an individual's preferences and job-characteristics, and we therefore cannot exclude that job-characteristics in an occupation or a workplace may still be important for individuals' mental health. To us, this appears an interesting residual explanation which we leave for future research, but we fully acknowledge the empirical challenge, even with access to better data, to test hypotheses related to individuals' preferences.

In what follows, Section 2 gives an overview of the data at our disposal. We then describe the incidence of mental illness in Sweden (Section 3) and high school applications for field of study in Sweden between 1977 and 1991 (Section 4). Section 5 describes the application data in more detail to explain the narrowing down of the data to our main analysis sample. Section 6 presents the empirical identification strategy. The main results are presented in Section 7, including estimates on mental health in adulthood of being admitted to the preferred field of study and the impact separated by field of study. Section 8 provides separate estimates by gender and by field of study. This is followed by a battery of stability checks in Section 9 while Section 10 presents additional analyses that seek to determine the most plausible mechanisms behind our results. Section 11 concludes.

2. Data

The analyses in this paper are based on population register data of all residents in Sweden from 1990 and onwards (the LISA database of Statistics Sweden), containing a wide range of socioeconomic outcomes, such as occupation, income, and highest educational level attained. Two additional registers are of particular importance. The first is that of applicants to Swedish high schools from 1977 to 1991. This encompasses 1.2 million individuals, and the records contain information on individuals' preference ranking of programs as well as their GPA. The second important data source is from the Swedish National Board of Health and Welfare, providing information on prescribed medications and overnight hospitalizations. The registers provide exceptional data quality in terms of low attrition rates and high accuracy.

We merge individual level application data with data on short-term outcomes such as completed field of study, and long-term outcomes such as records of prescribed medications and records of hospitalizations. Data on prescribed medications are available from 2005 to 2020, which means that our oldest cohort (born in 1961, applying to high school in 1977) is observed between ages 44 and 59, whereas the youngest cohort (born in 1975, applying to high school in 1991) is observed from age 30 to 45. Our main outcome variable will reflect the incidence of antidepressant prescriptions over the age window 40–45, with robustness checks using the age window 45–50 or 44–45, where the latter window is narrower but covers the only ages in which we can observe prescribed medications for all our cohorts. [7] Hospitalization data are available from 1997 to 2019, which means we can then observe all our cohorts within the age span of 36–44. In robustness checks, we use hospitalization separately for age windows 36–40 and 40–44. Hospitalizations due to mental disorders are rare and despite considering a relatively wide age window the mean incidence of hospitalization remains at 1.69% for our main analysis sample.

3. Mental health

In this section we first present some stylized facts regarding indicators of mental health in Sweden. In Sections 3.2 and 3.3 we introduce our data on mental health indicators, showing population averages across age. In Section 3.4 we merge the information with population data and the data on applications to high school, as this allows us to set our two different indicators of mental health in relation to GPA and annual earnings.

3.1 Patterns in depressive and anxiety disorders in Sweden

According to the Swedish National Board of Health and Welfare, depressive and anxiety disorders are the most common mental illnesses. They accounted for 9.7% of years lived with disability in 2019 relative to the global average of 8% across all countries.[8] Approximately 25% of the

[7] For the age windows 40–45 and 45–50, data need to be slightly adjusted for the youngest or the oldest cohorts. See note to Table A6.

[8] Depressive and anxiety disorders were once considered "diseases of affluence," but in fact the burden of these diseases is roughly similar in both high- and low-income countries.

Swedish population is at some stage in life affected by an anxiety disorder. While anxiety is equally prevalent among men and women, depressive disorders affect women more often than men. The risk of suffering from depressive disorders is 36% for women and 23% for men (Socialstyrelsen, 2021).

Depressive and anxiety disorders typically lead to a significant decrease in the quality of life and impaired work ability. [9] The recommended treatment options for mild and medium disorders are psychotherapy as the initial treatment (typically cognitive–behavioral therapy), and pharmacotherapy, or a combination of the two. Of the pharmacotherapeutic options, usually referred to as "antidepressants", the most commonly prescribed medicines are selective serotonin reuptake inhibitors (SSRIs). Although psychotherapy is recommended to be the initial treatment, official statistics show that approximately 70% of all patients diagnosed with these disorders in primary care units in Sweden were prescribed medication and only 20% received psychotherapy (Sveriges Kommuner och Regioner, 2019). This indicates that recommendations are not strictly followed, firstly because of a shortage of qualified personnel to offer psychotherapy, but also presumably in part because prescribing antidepressant medications is a less costly alternative.

3.2 Data on prescribed antidepressants

We have access to data on prescribed medications from 2005 to 2020. What we henceforth label "antidepressants" is defined as the incidence of prescribed medications within the Anatomical Therapeutic Chemical (ATC) code N06A.[10] This encompasses the most widely used medications for the treatment of both depressive and anxiety disorders. Between 2005 and 2020, the share of

[9] Statistics for the U.S. show that 80% of depressed individuals report some degree of functional impairment, and 27% report serious impairment of their work or home life (Pratt and Brody, 2008).

[10] According to the national treatment guidelines issued by The National Board of Health and Welfare (Socialstyrelsen, 2021), when treatment of depression disorders and anxiety disorders warrant medication, these should be within the ATC code group N06A.

the population aged between 16 and 65 that was prescribed antidepressants almost doubled from 6.5 to 11.8%, with the shares for women consistently about twice as high as those for men.

Panel A of Figure 1 presents the incidence of antidepressants in the Swedish population across age (16 to 65) and by gender (using the full period). There is a relatively steep increase in the incidence until age 25, and for women also around age 40. The incidence continues to increase across almost all age groups, even the older groups, but the slope is then generally flatter. This pervasive increase may reflect both the fact that mental health deteriorates with age, and that individuals who are prescribed antidepressants become more likely to be prescribed antidepressants again in the future. Indeed, among those who were prescribed antidepressants between age 15 and 17 in 2005, the incidence at age 29 to 31 was 44.0% compared with 11.6% among individuals with no antidepressants between ages 15 and 17. Figure A1 (panel A) shows the incidence of first-time prescriptions of antidepressants. The incidence of first-time prescriptions increases sharply in adolescence and reaches its peak in the late teenage years.

We consider being prescribed antidepressants as a proxy for mild and medium mental health disorders. While we acknowledge that a higher incidence of prescribed antidepressants may partly reflect an increased or a better access to medical services, it seems unlikely to reflect a positive outcome, as the consumption of antidepressant medication has been associated with several side-effects.[11] However, using prescribed antidepressants as a proxy for mental health may also underestimate the true incidence of mental disorders, if non-monetary barriers such as

[11] Antidepressants usually improve the symptoms of the conditions they are prescribed for, but long-term use of antidepressants can also have negative side effects such as weight gain, sexual dysfunctions, emotional numbness, increased risk of cardiovascular events and increased risk of death (Bet et al. 2013, Maslej et al. 2017). Also, whereas antidepressants do not create addiction, it has been shown that marginal patients treated with antidepressants are much more likely to continue taking antidepressants long-term (Currie and Zwiers 2021).

stigma hinder healthcare-seeking behavior. Stigma is considered a major obstacle to the provision of care for individuals suffering from mental illnesses (Sartorius 2007). Moreover, stigma around mental health disorders can also lead to discrimination against these individuals and even against their families, either in social settings or in the labor market (Overton and Medina 2008, Hipes et al. 2016) and even in the provision of physical care (Lawrence and Coghlan 2002, Henderson et al. 2014). For this reason, it is of interest to complement our analyses with an outcome that is less sensitive to selection.

3.3 Data on hospitalizations related to mental disorders

As an additional outcome, we examine hospitalizations due to mental disorders as a proxy for severe mental health conditions. Although treatment for mental illnesses typically occurs in an outpatient setting, acute mental health episodes can warrant hospitalization.[12] In these cases, care typically begins in the emergency room, and it is often a family member or law enforcement officer that brings the person to the premises. The potential to self-select into treatment (hospitalizations) should be substantially reduced compared with the self-selection into treatment with antidepressant medication. Our definition of the incidence of hospitalization is restricted to International Classification of Diseases 10th Revision (ICD10) codes linked to environmental and lifestyle/socioeconomic factors rather than to biological factors. It includes anxiety, depression, drug abuse, or sleeping/eating disorders, but excludes diagnosis related to schizophrenia, personality disorders or disorders of psychological development (see Appendix for details).

In panel B of Figure 1, the incidence of hospitalizations as defined above is presented across age and by gender. In contrast to antidepressants, the incidence of hospitalizations is at its

[12] Some common reasons for hospitalization related to mental illness are severe depression, suicidal behavior, ideations, or threats of suicide.

highest level in the early 20s and is relatively stable across age groups after the age of 30. Women have a higher probability of being hospitalized than men, but the gender gap is much smaller than for antidepressants. At age 40, women have an approximately 0.59% probability of being hospitalized for a mental health disorder, whereas men have a probability of 0.54%. Among those who were prescribed antidepressant medications between age 40 and 45, about one in nine (11.4%) were also hospitalized for mental disorders between age 36 and 44.

The incidence of first-time hospitalizations is shown in panel B of Figure A1. Similar to antidepressants, the incidence increases sharply in adolescence, peaking in the late teenage years or early 20s when individuals enter the labor market or enroll in college. The indication of path dependence in hospitalizations is even stronger than for antidepressants. Of those hospitalized due to mental disorders between age 15 and 17 in 1997, the incidence at age 29 to 31 is 14.8% compared with 1.8% among those who were not hospitalized previously.

3.4 Mental health, educational attainment, and income

Mental health exhibits a gradient in markers for socioeconomic status (SES), such as educational attainment and income. To be able to show supporting evidence for this claim, we now limit the descriptive statistics to the 1.2 million individuals who applied to high school between 1977 and 1991 (the population from which we will draw our main analysis sample).[13] Figure 2 presents both the share with prescribed antidepressants at age 40–45 and hospitalizations at age 36–44 (scale on right y-axis) by level of GPA. The GPA is a proxy for academic ability, with mean around 3 and where 5.0 is the highest possible value. Figure 2 shows that low levels of GPA at

[13] For this descriptive part of the paper, the advantage with the restriction is that we then have information on individuals' GPA in ninth grade. The limitation is that we exclude individuals who did not apply to high school, primarily at the lower end of the GPA distribution. The excluded individuals represent roughly 40% of the cohort enrolled in 1977 but gradually smaller fractions, and about 20% for the cohorts enrolled in 1985 or later.

age 16 are linked with higher incidence of antidepressant prescriptions and hospitalizations in adult age. Individuals with a ninth-grade GPA of slightly above 2 have a 20% probability of being prescribed antidepressant medication at age 40–45, compared with roughly 13% for individuals with among the highest ninth-grade GPA. For hospitalization between ages 36 and 44, the corresponding shares are 0.46% and 0.15%, respectively. We note that the relation between GPA and antidepressants is fairly linear, but that the negative slope between GPA and hospitalizations is decreasing in particular for low GPA levels.

Figure 3 presents the relation between annual labor earnings percentiles measured at age 42 and our indicators of mental health.[14] The relation is again clearly negative. The solid lines indicate that, between the 10th and 90th percentiles, the probability of being prescribed antidepressants decreases by two-thirds, and the probability of being hospitalized decreases by nine-tenths. Interestingly, if one accounts for GPA and year of birth, the negative relationship between income and mental health disappears to a large extent, as suggested by the almost flat dashed lines.

4. Setting

We now turn to describing the Swedish educational system, the curricula of the high school programs which we analyze, and the admission process to high school programs.

4.1 The Swedish educational system

The Swedish educational system includes compulsory school for nine years with very limited tracking. After the ninth grade, at age 16, individuals can leave school or apply to high school, where there is a choice of a number of programs. The applicant submits their application, stating

[14] Annual earnings percentiles are based on mean earnings observed at age 41–43. Age 43 is the highest age for which we observe annual earnings for all our cohorts.

a list of preferred programs. During the period of our study, between 1977 and 1991, around 70% of a cohort continued to high school. They chose between five academic three-year programs and up to 21 non-academic two-year programs. Roughly half (48%) were admitted to one of the academic programs and the others to one of the shorter non-academic programs.

The five academic programs, which are the focus of this paper, were Engineering (13.1% of the applicants), Natural science (8.6%), Business (13.0%), Social science (9.2%), and Humanities (4.4%). These were preparatory for higher education and about half of those completing an academic program also went on to complete a college major. As will be shown in Section 4.4, there was no clear hierarchy between the programs as they attracted students with only modest differences in average GPA. The non-academic programs were intended for individuals with lower GPA levels and included between 14 and 18 different vocational programs with a strong practical focus (e.g., Nursing, Office, Electronics). There were also three non-academic general programs (Social science, Business, and Engineering), which followed different curricula and were completely separate from the academic classrooms.[15] Completion of the general non-academic programs only qualified students for some shorter university programs but they could also later attend publicly provided adult education, which is a large sector in Sweden, to gain full eligibility for higher studies (see Stenberg 2022).

4.2 Contents of the academic programs

Table 1 presents the curricula of the five academic programs.[16] Each program was characterized by its main topic, so that Engineering included more technology-related subjects. Natural science

[15] Among individuals with an academic first choice, 27% had a non-academic second choice. Of those, 53% were general non-academic programs and 34% were for either Electronics, Office work or Nursing, and the remaining 13% were various other vocational programs.

[16] The curricula described remained stable during the period 1977–1991, but changed following a high school reform, which was gradually implemented between 1992 and 1994.

included more science classes and, compared with Engineering, also had a stronger focus on social studies and language. The Math classes in Engineering and Natural science were also at a more advanced level than in the other programs. The Business program set aside one quarter of the curriculum for Law, Accounting or other business-related subjects. Similarly, the curricula of the Social science and Humanities programs devoted more classes to Social studies and Liberal arts, respectively, with language comprising 43% of the curriculum for Humanities. Another difference was that the Engineering program had an optional fourth year. In contrast to the classroom studies of the first three years, 85% of the curriculum in the fourth year consists of lab exercises in the specialty chosen (Machinery, Chemistry, Construction, or Electronics). In general, the differences in curricula made it difficult to switch between programs. Once admitted, switching between academic majors was unusual, with only 4.9% completing a different academic major than the one that they were initially admitted to.

4.3 Application and admission to programs

In the spring semester of ninth grade, students applied to high school, which would start in the autumn. Individuals could typically not apply to a specific school but were restricted to applying to a program in the high school region where they resided. Individuals could therefore not apply to the same program in two different schools. The number of regions increased slightly during the period, from 115 regions in 1977 to 137 in 1991, and the median number of applicants in a region, in a specific year, was 927. The applicants competed for slots based on their GPA, which was the average grade from 10–12 subjects. The range of the GPA was limited by the fact that each subject grade is discrete from 1 (lowest) to 5 (highest). Added to the GPA was also a bonus of 0.2 if an individual applied to a program where they would be the minority gender (e.g., women to Engineering or men to Humanities). This adjusted GPA is what we refer to in the paper, unless stated otherwise.

Admissions to programs follow a so-called “serial dictatorship” process, where the central admission office admits individuals with the highest GPA to their first choices. Only one decimal of the GPA is considered, which means that ties are common. The individuals with the second-highest GPA are then assigned to their first choices if there are still slots available. Administrators then move on to the individuals with the third-highest GPA, and so on. If a program attracts more applicants than there are slots, the applicants with GPA below a cutoff in that region and that year are not admitted to the program. This process has been shown to be strategy-proof such that individuals will reveal their true preferences when applying for programs (Svensson, 1999).[17]

In July, the applicants receive a letter informing them whether they have been admitted to one of their choices or not. After this point, there is some re-shuffling of individuals between programs, which means that admissions do not exactly match actual enrollment. This may, for instance, reflect that students move to another region or change their minds, as it is possible to choose another program as long as there are still open slots. In case the program of their initial choice was oversubscribed, the transfer to another program will then open up a slot that can be filled by a student who was initially not admitted. Transfers between programs after admission may be non-random. We therefore use the admission cutoff GPA as our source of exogenous variation in program choice.

[17] Applicants during the period 1982–1984 received a bonus of 0.5 and 0.2 for their first and second choices, respectively. This makes it possible that individuals did not reveal their true preferences in their application ranking the programs. Our robustness checks presented in Section 9 include estimates where these years are excluded.

4.4 Outcomes of interest

We next provide descriptive statistics across fields of study. Figure 4 shows, in panel A, the average GPA at age 16 (black bars) and the average labor incomes at age 42 (gray bars, scale on the right y-axis) by field of study completers. There are only modest differences in average GPA between the academic programs, as they are close to identical for Engineering, Social science and Humanities, slightly lower for Business, and slightly higher for Natural science. The figure also shows that higher mean GPA is not always linked with higher mean earnings. For instance, the mean GPA in Natural science is higher than in Engineering, but the mean earnings among completers of Engineering are higher. The same is valid for Business and Social science, where Business on average has a lower mean GPA but higher earnings. Thus, there is no clear ranking between the academic fields. [18]

Panel B of Figure 4 displays the incidence of antidepressants at age 40–45 and hospitalization at age 36–44 for the completers of each field of study. The prescriptions for antidepressants by program type varies substantially, with a low of 9.1% for Engineering and a high of 19.4% for Humanities. The pattern across the programs is one that increases from left to right, that is, Engineering has the lowest incidence and Humanities the highest. This pattern is similar for the probability of hospitalization, even though the levels are much lower (right hand y-axis).[19] Variation in mental health across programs may, of course, reflect systematic differences in the underlying characteristics of the individuals. For instance, comparing the levels of average earnings from

[18] These patterns also hold if the sample is separated by gender, except that men completing Natural science have higher earnings than male completers of Engineering.

[19] Figure A2 in the Appendix shows that these patterns also hold if the analysis is done separately for men and women. Interestingly, despite the similarity in patterns between programs for men and women, the female applicants are overrepresented in Social science (72%) and Humanities (86%), programs associated with lower earnings and higher levels of prescribed antidepressants and hospitalizations.

panel A with the indicators of mental health in panel B suggests that earnings levels are negatively associated with our indicators of mental health, in line with what we saw in Figure 3. However, while individuals with different earnings typically differ in their levels of GPA, the academic programs are relatively similar in terms of mean GPA.

5. Main analysis sample

To define our main analysis sample, we impose a set of restrictions based on the application data. First, the analyses are limited to oversubscribed programs, that is, for each program, in a specific region and a specific year, we condition that there are more applicants than slots. There is no explicit information on GPA cutoff values, and these are instead inferred from the data. We limit our main analysis sample to specific year–region programs where there is a sharp cutoff, meaning that all individuals above a certain GPA threshold (our cutoff) are accepted and where applicants with a GPA below the threshold are not accepted. We also condition that there are at least 25 applicants accepted and at least three individuals not accepted.

Of the 1.2 million applicants, 48% stated an academic program as their first choice and, among those, about 60% also applied in a region and in a year where their preferred program was oversubscribed (326,211 individuals). We also restrict our main analysis sample to applicants with a GPA within a window of -0.5 and +1.5 points of the normalized cutoff, and condition that they list a second choice. [20] We further exclude individuals with a GPA exactly equal to the cutoff unless all individuals at the cutoff were admitted. This is because we do not have information on how administrators would break ties in the admission process, and decisions on who to accept

[20] In 96% of the cases applicants were admitted either to their first or their second choice. If admitted to their third ranked choice, or lower, the choice with the lowest GPA cutoff above their accepted choice is considered as their preferred first choice.

and not accept exactly at the cutoff could be non-random.[21] Finally, we exclude those who were not observed in the population registers between age 40 and 43. The 247,074 individuals remaining constitute our main analysis sample. Table 2 provides descriptive characteristics of this sample alongside a similarly conditioned sample based on individuals who applied to academic programs that were not oversubscribed. There are only modest differences between these two samples. Table A1 in the Appendix also provides these statistics by first-choice program.

Figure 5 presents the distribution of GPA in our main analysis sample (gray columns), together with the distribution of the cutoff GPA in oversubscribed academic programs (white columns with borders).[22] The average cutoff in our sample is 3.38, which roughly corresponds to the 60th GPA percentile in the population of ninth graders. However, in our main analysis sample, which consists only of applicants to academic programs, the average cutoff corresponds to the 17th percentile. Figure 5 also shows that most of the applicants in our sample are to the right of the cutoff. This reflects the fact that the majority of individuals with a low GPA state a non-academic program as their preferred choice and are therefore excluded from our main analysis sample (non-academic programs are generally smaller and seldom oversubscribed). Non-academic programs were intended for low GPA students, and this is reflected by the fact that, among individuals with a GPA below 3.0, more than 90% applied for a non-academic program as their first choice. Conversely, among individuals with a GPA above 4.0, more than 90% listed an academic program as their first choice. Therefore, with our cutoffs centered around 3.4, it is not certain that

[21] In cases where there is no mix of accepted and non-accepted, we define the cutoff as the average between the two neighbouring GPA values. For example, the cutoff is defined as 3.45 if everyone at 3.5 was admitted and everyone at 3.4 was not admitted.

[22] Individuals with a GPA above 5.0 reflect the gender bonus as well as the bonus system in place from 1982 to 1984. See Section 3.3 for details.

a marginal individual is better off if they end up in an academic program (see Silliman and Virtanen 2022).

The mean cutoff levels across the academic programs only differ by 0.19 (at most), and Figure A3 in the Appendix also shows that the cutoff distributions are similar across programs. [23] The central guidelines stipulate that class size of academic programs should be set to a maximum of 30 students. In the hypothetical case of one class and 40 applicants, the program will be oversubscribed with a cutoff equal to the GPA of the 30th applicant. If, in the following year, the program again attracts 40 applicants but the region decides to expand the program to two classes, there will be 60 slots (2x30), and everyone will be admitted. Thus, a program may be oversubscribed in one region but not in another, and it may also be oversubscribed in a specific region in one year, but not the next year. In practice, this means that applicants do not know if the cutoff of a certain program will be lower or higher than some other program. [24]

6. Empirical strategy

6.1 Regression discontinuity (RD) model

To elicit causal estimates of the effect of field of study assignment on indictors of mental health, our estimation framework is a regression discontinuity (RD) model. The running variable is defined as the distance between the cutoff GPA and the GPA of the applicant. An early example of this approach is found in Jackson (2010) and more recently in Butikofer et al. (2023), in both

[23] The mean cutoff is 3.36 for both Engineering and for Business, 3.47 for Natural science, 3,55 for Social science and 3,50 for Humanities.

[24] Table A2 in the Appendix reports the fraction of years with a higher cutoff for one major compared to another, within the same school region. For example, Engineering has a higher cutoff than Natural science in 37% of the cases, but a lower cutoff in 25%, and in the remining years they both have open enrollment or, less commonly, the exact same cutoff.

cases seeking to estimate the causal effect of attending a better school by exploiting the fact that assignment varies around a test score or GPA cutoff.

We first consider the reduced form RD, where we have a sharp cutoff. The basic idea of this model is to compare outcomes of individuals with almost identical backgrounds but with large differences in the probability of being admitted to a program. The reduced form RD can be written as

$$y_{stp} = 1[x < c_{stp}]g^{l}(x - c_{stp}) + 1[x > c_{stp}]g^{r}(x - c_{stp}) + 1[x > c_{stp}]\theta + w'\gamma + e_{stp}$$

For convenience, we omit subscript identifying individuals. The running variable is the distance between applicants' GPA (= x) and the cutoff (c_{stp}) for each school region (s), each year (t) and each program (p). The first part of the equation considers GPA values below the cutoff, the second part GPA values above the cutoff, and w is a set of pre-determined controls that include dummies for applicants' first choices as well as second choices, application year fixed effects, region fixed effects and parental background characteristics (see Table 2). The main coefficient of interest is θ, which reflects the impact of being admitted to the preferred field of study on outcome y, which is an indicator of adult mental health.

The estimation of the model as presented is extremely data demanding, as cutoffs vary for each program across time and across regions, and for each year–region program there are five different first choices (above the cutoff) and more than 20 different second choices (below the cutoff). To gain precision, we will follow earlier work by normalizing the cutoffs to zero, to make it possible to pool the data into a single regression (Jackson 2010, Kirkeboen et al. 2016, Butikofer et al. 2023, Dahl et al. 2023). Our baseline model for antidepressants allow slopes to differ between each first choice, which means we estimate five different slopes. For hospitalizations, the benchmark model also includes seven program (second-choice) specific squared terms to the left the cutoff, to account for a decreasing slope for low GPA individuals (see Figure 2). [25]

An important condition for the RD design to be valid is that the running variable cannot be manipulated around the cutoff. In the present setting, that is unlikely to occur since the GPA is determined as the average of subject-specific GPAs and, more importantly, the cutoff varies across years, regions, and programs. As illustrated in Figure A4, the distribution of first differences in cutoff by year (for a given program and region) shows substantial variation. Only in 17% of the cases is it the same two years in a row. Another way to check for manipulation is to test if pre-determined characteristics are balanced around the cutoff. As shown in Figure 6, there are no jumps around the cutoff, as confirmed by formal tests presented in Table A3.[26]

6.2 Fuzzy RD

As presented, the estimates of θ from the reduced form model will capture the causal impact on mental health of admission to the preferred field of study in high school. Within a fuzzy RD framework, we also apply the sharp cutoff for admission as a first stage instrumental variable estimate of the probability of enrollment, or of completion, to estimate the impact of enrollment as well as of completion of a program on mental health. Figure 7 illustrates how the share admitted,

[25] These specifications compare well with earlier contributions concerned with fields of study. Kirkeboen et al. (2016) similarly restricted slopes by choice category to be the same on both sides of the cutoff but used instrumental variables (IV) instead of RD to gain precision. Dahl et al. (2023) applied a baseline RD model with two slopes, assuming a single slope for all first choices to the right of the cutoff and a single slope to the left of the cutoff for all second choices. Our robustness checks include specifications which further expand the number of slopes.

[26] One may note that a test based on smoothness in the density around the cutoff of the running variable, proposed by McCrary (2008) and Cattaneo et al. (2018), is not applicable in the present setting. This is because a normalized cutoff of zero creates a spurious discontinuity in the density when the cutoff is based on a rank-order statistic. Current work by Cattaneo, Dahl, and Ma seeks to modify a density test to account for this (Dahl et al. 2023, page 365).

enrolled, and completed varies by the running variable. Panel A of Figure 7 shows the sharp cutoff for admission, whereas the shares enrolled or completing the first-choice program are, as discussed in Section 4, not perfectly predicted by admission. To explain the upward slope to the left of the cutoff in panel B of Figure 7, imagine a case where there are three Engineering classes, with 90 students in total admitted and, say, ten individuals immediately to the left of the cutoff. If four of the 90 admitted individuals do not enroll (e.g., because they change their minds or move to another region), it will open up four slots and four out of the ten applicants (40%) to the left of the cutoff will enroll and perhaps complete the track of their first choice, the one that they initially were *not* admitted to.

Enrollment and completion among applicants who were initially not admitted may be endogenous, which is why we use admission as the first stage IV. However, identifying the causal effects of enrollment or completion then requires three additional assumptions. First, *monotonicity* implies that if the GPA of an applicant ends up above the cutoff (on the right side), it does not make the applicant less likely to complete the first-choice major. This assumption seems innocuous in our framework. Second, *the exclusion restriction* requires that if an applicant ends up above the cutoff, the outcome of interest (in our case, mental health) will only be affected by the completion of that program. It is possible that admission to a program has an independent effect on the outcome if individuals tend to systematically switch to some other program, or if admission to a specific program increases the likelihood of dropping out of high school. However, less than 10% of the applicants complete a different program than the one they are admitted to, and due to the differences between the curricula of majors (see Table 1) switching is most likely to occur within the first semester.[27] Concerning the likelihood of dropping out of high school, 6.4%

[27] In our main analysis sample, of those who switch to complete another major than the one they are initially admitted to, 4.7% complete a non-academic major and 4.8% a different academic major.

of the applicants in our main analysis sample did not complete any major. Reduced form estimates indicate no statistically significant effect of admission on the probability of dropping out (p-value .597).

Third, *the irrelevance condition* requires that, if an applicant ends up above the cutoff, and it does *not* influence the probability of completing the first-choice major, it should not influence the probability of completing any other major either (see Kirkeboen et al. 2016). Even though this assumption is not possible to test regarding enrollment or completion, it seems likely to hold in our setting. One indication of this is that the irrelevance condition holds by construction when we apply our reduced form model, since we have a sharp cutoff in that case, and the reduced form estimates are qualitatively close to identical with our IV estimates.

7. Main results

7.1 First stage results

Panel A of Table 3 presents the first stage regression results of the baseline models. The outcomes are binary variables for whether applicants enrolled or completed their first-choice major, as a function of whether their GPA exceeded the admissions cutoff. The estimates indicate a substantial increase in the probability of enrollment or completion of the first-choice field of study for individuals who are admitted. Panel B of Table 3 also presents these estimates separately by first-choice field of study. All estimates are statistically significant, and vary from .5225 to .7315 for enrolment and from .3665 to .5584 for completion. In what follows, we present estimates applying (1) the sharp RD reduced form estimates, (2) fuzzy RD estimates for program enrollment ("IV-enrolled"), and (3) fuzzy RD estimates for program completion ("IV-completed").

7.2 The impact of preferred field of study

We first consider whether admission to the preferred field of study (irrespective of what field) impacts mental health. The probability of being prescribed antidepressants and the probability of hospitalization due to mental disorders are used as outcomes in separate analyses. As discussed in Section 3, these are likely to be different in terms of self-selection (access to healthcare), and we also interpret antidepressant prescription primarily as an indicator of mild or moderate mental disorders, whereas the incidence of hospitalizations reflects more severe mental health problems.

Table 4 presents our baseline model estimates of the effect of being admitted to the preferred field of study on the incidence of prescribed antidepressants when aged 40 to 45 (panels A and B) and on hospitalizations due to mental disorders when aged 36 to 44 (panels C and D). Figure 8 also provides graphical illustrations of the incidence of antidepressants (panel A) and of hospitalizations (panel B) by the distance to the cutoff GPA.

The results for antidepressants indicate that individuals admitted to their first choice have a 0.66 percentage point lower probability of being prescribed antidepressants between ages 40 and 45. The corresponding estimate for completion is -1.35 percentage points which represents 8.4% of the mean as measured for applicants within +/- 0.2 of the GPA cutoff. Since about one in four (27%) had a non-academic second choice in our main analysis sample, the results could partly be driven by the number of years of schooling rather than by gaining access to the preferred field of study. In panel B we apply interaction terms to split estimates depending on the second choice, but the coefficient estimates then tend to be closer to zero if the second choice is non-academic (equality of the coefficients cannot be rejected, reduced form p-value .208).

Turning to hospitalizations, the reduced form estimates of being admitted to the preferred field of study decreases the probability of being hospitalized due to mental health disorders by

0.36 percentage points. The corresponding estimate for completion is a 0.77 percentage point reduction. This estimate represents 40% of the mean (0.0193) as measured for applicants within +/- 0.2 of the GPA cutoff. It implies that access to the preferred field of study in adolescence has a large impact on reducing the probability of suffering from severe mental disorders in adulthood. However, since hospitalization is a relatively rare event, the estimated impact in terms of percentage in relation to the mean around cutoff should be interpreted with caution. When estimating the impact separately for those with academic or non-academic second choices, we again find estimates to be closer to zero if the second choice is non-academic. When interpreting these results, it is useful to keep in mind that the curricula of non-academic programs were adjusted to individuals with a low GPA. The validity of our estimates pertains to individuals around the cutoff, that is, with a GPA around the 60^{th} percentile rank, a margin where it is not obvious whether an academic or a non-academic program would be the most appropriate.

7.3 The impact of field of study on mental health

Table 5 presents estimation results pertaining to the impact of each specific field of study on our indicators of mental health. Figures 9 and 10 also provide graphical illustrations of the program specific variation in antidepressants and hospitalizations by the distance to the cutoff GPA. Panel A of Table 5 shows the estimated effects on the probability of prescription of antidepressants. Individuals completing their first choice of Engineering have a 2.87 percentage point lower probability of being prescribed antidepressants between ages 40 and 45. This is a sizable effect of 27% when compared with the mean among applicants to Engineering within 0.2 GPA points of the cutoff. A statistically significant effect at a 10% level is also found for completers of Business majors, which suggests that completing Business reduces the probability of being prescribed antidepressants by 1.64 percentage points (10% of the mean). The estimated effects of completing

Natural science and Social science are negative but statistically insignificant. In contrast, for a Humanities major, we find the opposite sign effect, significant at a 10% level, and implying a 5.23 percentage point higher probability of being prescribed antidepressants (23% relative to the mean).

Panel B of Table 5 presents results by field of study on the incidence of hospitalization due to mental disorders at age 36–44. These estimates reflect the incidence of more severe mental disorders, which are possibly less influenced by factors related to access to healthcare, by stigma, or what is socially accepted. We find again that completion of Engineering and Business majors has a significantly negative impact, thus lowering the probability of being hospitalized. The effects are large. For Engineering, the reduced form coefficient of .0066 corresponds to 46% of the mean around +/- 0.2 of the cutoff, and the IV estimate of completion is even at the level of the mean. The estimate for completion of Business represents 41% compared to the corresponding mean. However, as already mentioned, interpreting the estimated impact in relation to the low mean incidence of hospitalization should be done with caution. For Humanities, where we saw increases in the probability of being prescribed antidepressant medication, the point estimates on hospitalizations are again positive but now statistically insignificant. Except for Natural science, the pattern in the results for hospitalization show many similarities with panel A and the probability of being prescribed antidepressants.

F-tests for the hypothesis of joint equality of the coefficients cannot be rejected, either in the case of antidepressants or in the case of hospitalizations (p-values for IV-completed are .143 and .313 respectively). If we instead perform the tests separately by program, we find statistically significant differences for humanities in the case of prescribed antidepressants, in relation to all the other programs.

Table A4 in the Appendix consider the hypothesis that the results in Table 5 are driven by years of schooling rather than curricula, by presenting estimates which separate between individuals with two-year non-academic second choices and other academic second choices. The coefficient magnitudes indicate no support, for any of the five programs or the two outcomes, that the number of years of schooling is the main driver of the results.

Although very data demanding, it is technically possible to estimate separate coefficients for each of the 30 possible first-second-choice-combinations.[28] For completeness, these are presented in Appendix Table A5 for both antidepressants and hospitalizations. The third column states for each first choice the share of individuals with the second choice in question. At face value, the coefficient estimates contain information about what our results in Table 5 reflect, but they are overall too imprecise to allow for a detailed analysis. However, what these results indicate is that the results in Table 5 are generally not driven by specific second choices (which is also seen from Table A1). Indeed, if individuals act on their comparative advantages, estimates may well to go in the same direction whether program X is chosen ahead of program Y, or vice versa. To take an example, the estimates for antidepressants are negative for individuals with Natural science first and Business second, as well as for individuals with Business as first choice and Natural science as second choice. In this case, the sum of the coefficients is negative and statistically significant from zero, which is consistent with that individuals act on their comparative advantage (p-value .001). This is also the case for the combination involving Natural science and Social science (p-value .006). In fact, the sum of the point estimates is often negative and thereby

[28] Earlier studies typically do not present specific first-second choice estimates (e.g. Bleemer and Mehta 2022, Britton et al., 2022, Kirkeboen et al. 2016), though Kirkeboen et al. present first-second choice estimates where at least 33 fields of study are collapsed into nine fields.

consistent with this interpretation, but the standard errors are too large to reject that the sum of the coefficients is different from zero.[29]

8. The impact by gender

In Section 3, we saw that mental disorders are generally more common among women. A natural question to ask is whether the impact of field of study is similar or different across gender, even though a caveat is that precision suffers as we slice the data into smaller subsamples. In the following, we apply the baseline model specifications, estimating separate coefficients for men and women.

8.1 Impact on the incidence of antidepressants

Table 6 presents estimates by gender on the incidence of antidepressant prescriptions at age 40–45. For women, the overall effect of completing the preferred field of study is a 2.67 percentage point reduction in the probability of being prescribed antidepressants in adulthood. It corresponds to a decrease of 12% compared with the mean around the cutoff. For men, there is no overall significant effect but, as will be shown in a moment, this is in fact the result of offsetting effects of different fields of study. A formal test rejects equality between the coefficients for women and men (reduced form p-value .007).

Turning to the estimates by field of study, both men and women who graduate from Engineering experience positive effects on mental health, and the estimated magnitudes relative to the mean are similar (27% for women, 30% for men) although the point estimate is larger for

[29] It is also useful to keep in mind that for a specific program, each second choice represent a unique selection of individuals. For instance, individuals choosing Business first and Engineering second are likely to be different from individuals choosing Business first and Humanities second.

women. Equality of the coefficients between men and women cannot be rejected for Engineering (p-value .145) but are otherwise clearly rejected (p-values below .02). Regarding the programs with a more even gender composition, the estimates for Natural science and Business suggest positive effects on mental health for women, which correspond to 29% and 16% respectively, though the results for Natural science are only significant at a 10% level. For men there are no statistically significant effects for either Natural science or Business.

In the female-dominated programs, the estimates for women in Social science imply a reduction in the incidence of antidepressant prescriptions, but the estimates are not statistically significant at the conventional 5% level (reduced form p-value .071 and p-value of IV-completed .128). The estimates of Humanities are in the opposite direction, indicating worse mental health, but not statistically significant. For men, both these programs are associated with positive estimates, which imply worse mental health. The estimates for Humanities are particularly large, and statistically significant, as the reduced form estimate corresponds to 32% relative to the mean, but these estimates are imprecise as only 1.9% of the male applicants stated Humanities as their first choice.

8.2 Impact on the incidence of hospitalizations

Table 7 report results by gender for the hospitalization outcome. For women, the estimate of completing the preferred field indicates a 0.68 percentage point reduction in the probability of hospitalization between ages 36 and 44 (significant at a 10% level), corresponding to 29% of the mean. For men, the coefficient reflects a 0.84 percentage point decrease in hospitalization, which represents 54% of the mean. A test for equality between the coefficients of women and men cannot be rejected.

For the specific fields of study, the estimated effects for Engineering are large for both men and women but, with relatively few women in Engineering, the estimates are statistically insignificant (p-value .119). For men, the reduced form estimate represents 49% relative to the mean, similar to what we saw in Table 5, and with the scaled-up IV estimate of completion comparable to the level of the mean (the lower bound of the confidence interval corresponds to 33% of the mean). For Business majors, the coefficients for women and men are similar in magnitude relative to the mean, at 43% and 41% respectively (for men only significant at a 10% level). For the other programs, there are no statistically significant effects although the estimates for Humanities, which tended to increase the probability of being prescribed antidepressant medication, are overall in the same direction as for antidepressants. Tests for equality of the coefficients between men and women cannot be rejected. To sum up, we find significant gender differences for prescribed antidepressants but no gender differences in the effects on hospitalization.

9. Robustness of the results

We assess the stability of our findings by first altering the baseline specification or our main analysis sample. This is followed by falsification tests where we use "fake cutoffs", and set out coefficient estimates in relation to those presented in Tables 4 and 5. Third, we apply different definitions of our outcome measures, by varying the age spans when measuring antidepressant prescriptions and hospitalizations.

Table 8 presents our baseline results in the first column followed by a battery of checks where we alter the baseline specification, or our main analysis sample. The second column shows estimates where we exclude the demographic controls. The third and the fourth columns are based on different samples: *i*) individuals within a narrower bandwidth around the cutoff and *ii*) excluding individuals who applied to high school between 1982 and 1984, when they were given a 0.5 GPA bonus for their first choice and a 0.2 GPA bonus for their second choice (see Section 3). In the fifth column, we reverse the specifications so that the baseline specification for antidepressants is applied for hospitalization and vice versa. Columns 6, 7 and 8 allow for increasingly flexible specifications.[30] In the final column, we include dummies for 30 potential first–second choice-specific intercept terms. The results are qualitatively the same across the board, although we sometimes lose statistical power when the sample is reduced or when the number of slopes to be estimated increases. For baseline estimates with p-values below .10 (first column), the point estimates are generally within one standard error of the alternative estimates.

We next provide falsification tests of our baseline RD model using "fake" cutoff values. The fake cutoffs applied are all to the right of the true cutoff to avoid the true cutoff affecting these estimates. We would expect these estimated coefficients to vary around zero. Figure 11 provides graphs of the distribution of these placebo estimates, applied for the seven margins with p-values below .10 in Tables 4 and 5. The vertical lines in the graphs represent the respective causal estimates from our main analysis. These are all extreme values compared with the placebo estimates, which indeed vary around zero. This exercise indicates that finding the magnitude of our estimates on mental health in Tables 4 and 5 is unlikely to occur simply by chance.

As an additional check, Tables A6 and A7 in the Appendix present results based on measures of mental health at alternative age spans. For antidepressants, estimates in Table A6 are based on the age bracket of 45 to 50 (panel A) or measured at ages 44 and 45 (panel B), the only two ages at which we can observe all our cohorts (see Table note). Table A7 shows the estimated

[30] The 10-slope model apply one slope for each of the five different first choices and also separately for men and women. The 24-slope model applies gender specific separate slopes for the five first choices to the right of the cut-off, for the seven second-choices to the left of the cutoff. The 60-slope model includes separate slopes to the left and right of the cutoff for each of the 30 first-second choice combination. All models include a left side squared term.

effects on hospitalization, separately for ages 36–40 and 40–44. The implications from the earlier findings overall, as well as for Engineering and Business, remain similar and statistically significant. The estimates indicate that the choice of age span is not of foremost importance for our main results.

10. Mechanisms

Our main results in Tables 4 and 5 convey evidence that gaining access to the preferred field of study influences mental health in adulthood. In this section we consider potential mechanisms behind these effects, originating from school-age and adulthood.

10.1 School-age mechanisms

School-age is a sensitive period in life and, due to path dependence, events in adolescence can hypothetically affect mental health in adulthood (Hardeveld et al. 2010, Buckman et al. 2018). First, in our context, the immediate disappointment of being denied access to the preferred field of study could influence our results. If that is the case, one would expect all programs to have the same effects on mental health. However, F-tests of the hypothesis of joint equality between coefficients are rejected when performed separately for women and men (p-values of .086 and .006 respectively, see also Section 7.3).

Earlier studies have suggested that mental health is affected by peer characteristics in school, including negative shocks in own ability rank (Kiessling and Norris 2023), female share among peers (Getik and Meier 2022) and peer ability levels (Butikofer et al. 2023). Table 9 report results based on proxies of the three suggested peer-characteristics. The estimates reflect the impact of being marginally admitted to a first-choice field of study at the year–region-program level.[31] The first column regards the effect on the student's own GPA rank which, because of our research design, indicate negative shocks to the relative rank since the marginally admitted have the lowest GPA. The second column shows that admittance to the first-choice program yields a small increase in the share of female high school peers. A lower GPA rank and higher female share would imply effects in the opposite direction compared with our baseline estimates. The third column consider peer quality, as we proxy the share of high-ability peers with the share of peers in the program–region year who (later) graduate from college. The estimates imply that being marginally admitted to a first choice increases this share, hence higher-ability peers. This estimate is in line with the baseline estimates, as an increase in high ability peers would imply better mental health. However, the largest estimates in column 3 pertain to students admitted to Social science (.19) and to Natural science (.30). For these two programs, the estimates on adult mental health were not statistically significant, and for Natural science sometimes not even with a negative sign. Taken together, the results in Table 9 indicate no or limited support for the school-age mechanisms, and we exclude that they constitute the main drivers behind the results reported in Tables 4 and 5.

10.2 Adult age mechanisms

To explore if outcomes in adult age serve as mechanisms behind out results, a caveat is reverse causality, for example that mental health may cause labor market outcomes as well as the other way around. To address this, we use data from the entire Swedish population to elicit information as to what extent a given characteristic in a given cohort is associated with mental health disorders. As an example, consider earnings rank and our outcome antidepressant prescription at

[31] Year–region program corresponds to a classroom in cases where there is one single class for the field of study in the region. In our sample, the median number of students accepted to a program in a specific region and year is 54, which implies two classes and slight measurement errors in the outcome variables applied in Table 10.

age 40–45. To get an estimate of how prevalent antidepressants are within each earnings rank, we first assign for each cohort (= year of birth), and each earnings rank as of age 42, the mean incidence of antidepressant prescription when aged 40–45. Importantly, this is an expected value based on data of the full Swedish population, for each cohort, and a leave-out-mean (i.e., the individual is left out of the calculation of the mean). We create one value for each half percentile, so 200 categories in total. We then assign each individual the expected value associated with their particular earnings rank at age 42 for each particular cohort. If the cohort earnings rank fully explains our estimates, we expect that the results obtained when using this expected incidence of antidepressant prescriptions as outcome, will be close to the estimates presented in Tables 4 and 5. We assign similarly calculated leave-out-means (= expected values) to account for employment uncertainty by setting expected values of antidepressants based on the number of years an individual has had at least one day of unemployment between age 33 and 43 (12 categories). To account for job-characteristics, we also do the calculations for 327 specific occupation categories within each cohort and for 19,594 workplaces with at least 10 employees. For hospitalizations, the identical procedure is repeated for all our calculations of leave-out-means.[32] [33] We also consider family formation in the shape of 16 different categories by cohort (married, if the number of children is 0, 1, 2 or more, and by gender).

Table 10 presents the reduced form estimation results when we use the constructed expected values as outcome variables (means and standard deviations of these outcome variables are presented at the bottom of the table). The outcome in panel A is the expected value (the

[32] Unemployment days is available from 1994, when our oldest cohort is 33 years old, hence the age interval 33-43. As for occupations, Statistics Sweden changed their coding of occupations in 2014, which means we define occupation as observed by age 38 as a proxy for occupation when aged 40+.

[33] A more conventional mediation analysis is to insert categories as dummy variables in our baseline specifications and check to what extent this affects our estimates. This yields only marginal changes compared with Tables 4 and 5, but a disadvantage with that approach, besides the endogeneity, is that the dummies only account for the variation in mental health by category as measured within our main analysis sample.

leave-out-means) of antidepressant prescription incidence and in panel B the expected value of hospitalizations due to mental disorders. The first column reports the baseline results as a point of reference. In the second column, the outcome is the assigned expected value within cohort and category of family formation. These estimates are modest relative to the baseline results. In the third column, the outcome is the assigned expected value within cohort and earnings rank. The point estimates reach 39% of the baseline estimates for antidepressants (.0026/.0066 = 39%) and 34% for hospitalization (.00122/.00356 = 34%). [34] The only outcome which is close to this mediating impact is, for antidepressant, the yearly employment uncertainty, defined as the frequency of yearly unemployment incidence between age 33 and 43 (.0021/.0066 = 32%). Because 73% of the sample are in the category with zero incidence, the variation stems primarily from individuals in the lower half of the earnings distribution. The mean earnings of those with non-zero incidence corresponds to the 30th percentile of the sample. In the fifth and sixth columns, the outcome variables are based on the expected mental health given the individuals' occupation and workplace, respectively. These estimates are closer to zero.

In sum, earnings explain roughly 40% of our estimated effects for antidepressants, but the other mechanisms considered are unlikely to drive our main estimates. That said, there is an enormous body of correlational studies that emphasize the significance of job-characteristics for mental health. These studies, mainly in sociology, management and psychology, concern employees' *perception* of their working environment and their job-tasks (e.g. Baumeister and Leary 1995, Hackman and Oldham 1980, Ryan and Deci 2000, Deci et al. 2017). While our register

[34] A similar impression is given by directly comparing the 30 estimates on mental health in Table A5 with those on earnings, in column 4 of Table A5. When we regress the 30 coefficients in the first two columns against the 30 earnings estimates the R-squared is .44 for antidepressants and .27 for hospitalization (weighted by the inverse of the of squared standard errors of the baseline model estimates).

data on occupation and workplace leaves some room for measurement error in terms of the quality of job-characteristics, the individual's perception of her job-characteristics is likely even more difficult to capture, serving to dilute the estimates. This is because our cohort–occupation specific expected values do not capture how well individual preferences match with the characteristics of their particular occupation or workplace. Based on the results in Table 10, we therefore cannot exclude that occupation and/or workplace may still be important for individuals' mental health. The many potential hypotheses suggested in the literature on job-characteristics (e.g. intrinsic motivation or perceived managerial support[35]) are basically untestable with register data, and even with access to better data it would be challenging to assess how perceived job-characteristics and mental well-being varies by field of study. We leave such analyses for future research.

11. Concluding remarks

Mental disorders are widely acknowledged as an important social problem and adolescence is a period of particular relevance when it comes to behaviors and events that can shape long-term mental health. One of the most important decisions an individual makes in adolescence is the choice of field of study, but the causal effects of field of study choice on mental health have, to our knowledge, not been studied. The contribution of the present study is to examine whether there is a causal link between eligibility to the preferred field of study during high school and mental health in adulthood. We find that students marginally admitted to their preferred field of study have a significantly lower probability of being prescribed antidepressant medication almost

[35] In the psychological literature, the individual's perception of three concepts have emerged as key: how the individual perceives her competence, her autonomy and her relatedness (or belongingness), which are all assumed to enhance mental health.

three decades after high school enrollment. We also find an even larger impact on hospitalizations due to mental disorders, presumably reflecting a lower risk for severe mental illnesses.

Our results contribute to the understanding of the socioeconomic determinants of mental disorders, but to fully address this issue in practice we need more specific knowledge about the underlying mechanisms of mental disorders. To this end, our mediation analysis conveys three general findings. The first insight is that peer characteristics in high school suggested as important for mental health in earlier studies, such as GPA rank, peer ability level, and the female share among peers, are less important in our context. The second is that annual earnings account for around 40% of the estimated effects. The third insight is that a relatively large portion of the remaining variation appears unexplained by the variation in observable data. In our view, an interesting path for future research would be to further explore how the relation between job-characteristics and mental well-being varies by field of study. It would connect not only with economics, but also with a vast literature in sociology, management and psychology.

As for policy, many countries apply regulations to restrict individual choices to fields of study, by setting limits on the number of slots for particular fields of study. This is to improve the efficiency of human capital allocation from the point of view of the society. However, the present study highlights that we may have underestimated the costs associated with restrictions on individuals' choice set.

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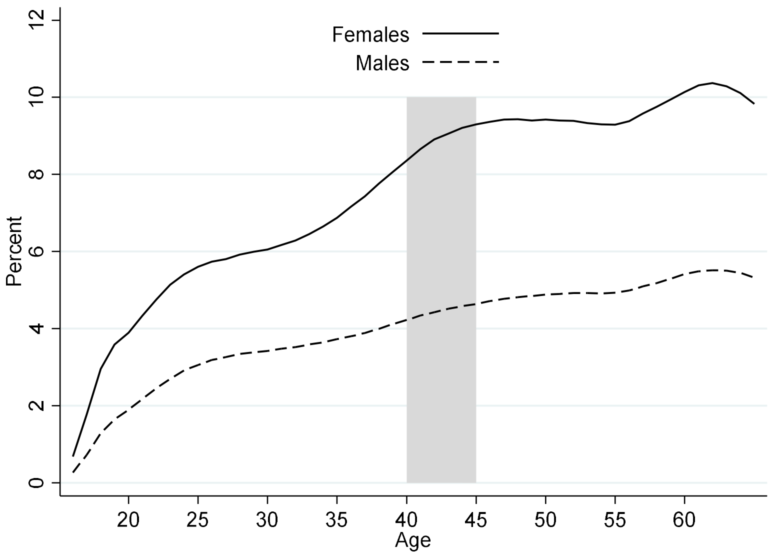
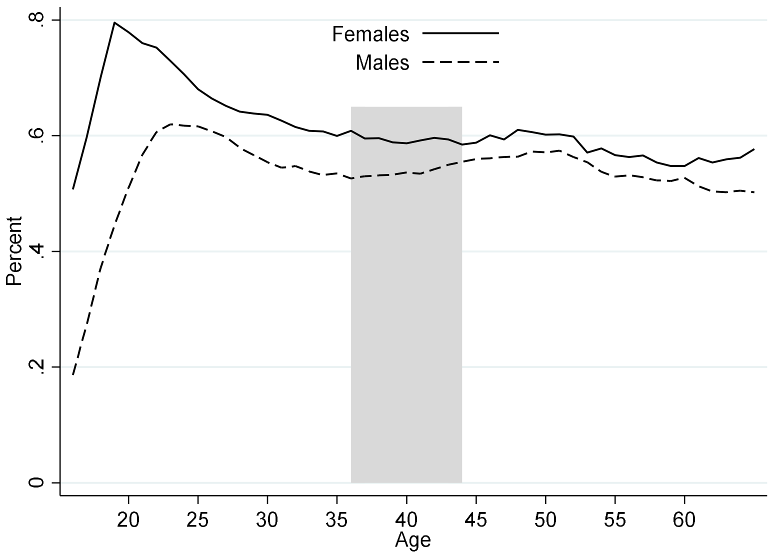
Figure 1. Total population indicators of mental disorders across age.

Panel A: Incidence of antidepressants



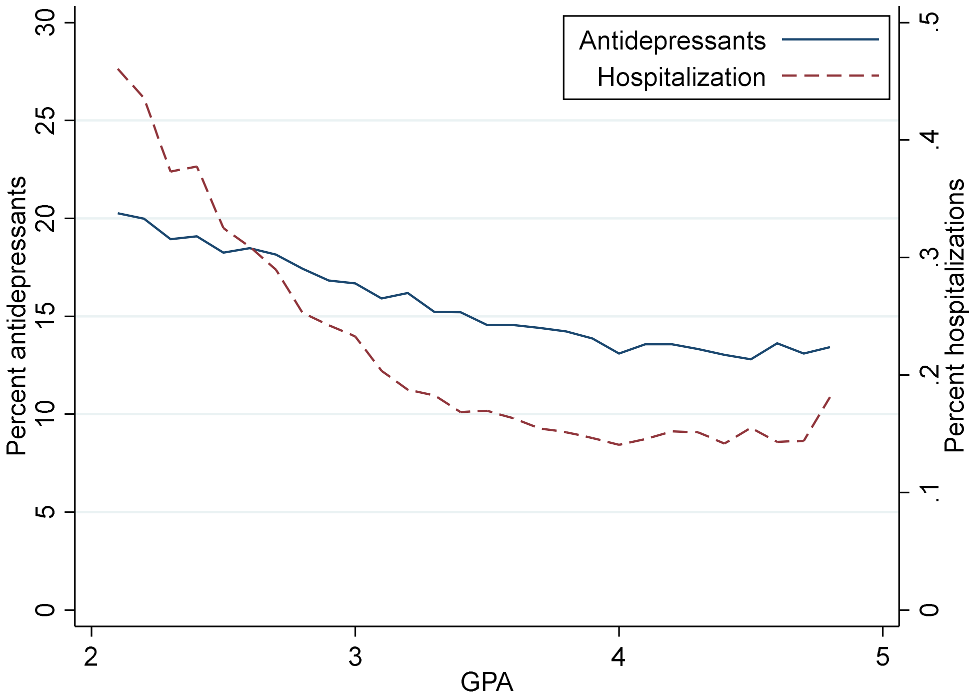
Notes: Total population incidence of prescribed antidepressant medications, averages across age based on observations 2005 to 2020. The shaded area represents the age limits of the measure for our baseline analyses (age 40-45).

Panel B: Incidence of hospitalization due to mental disorders



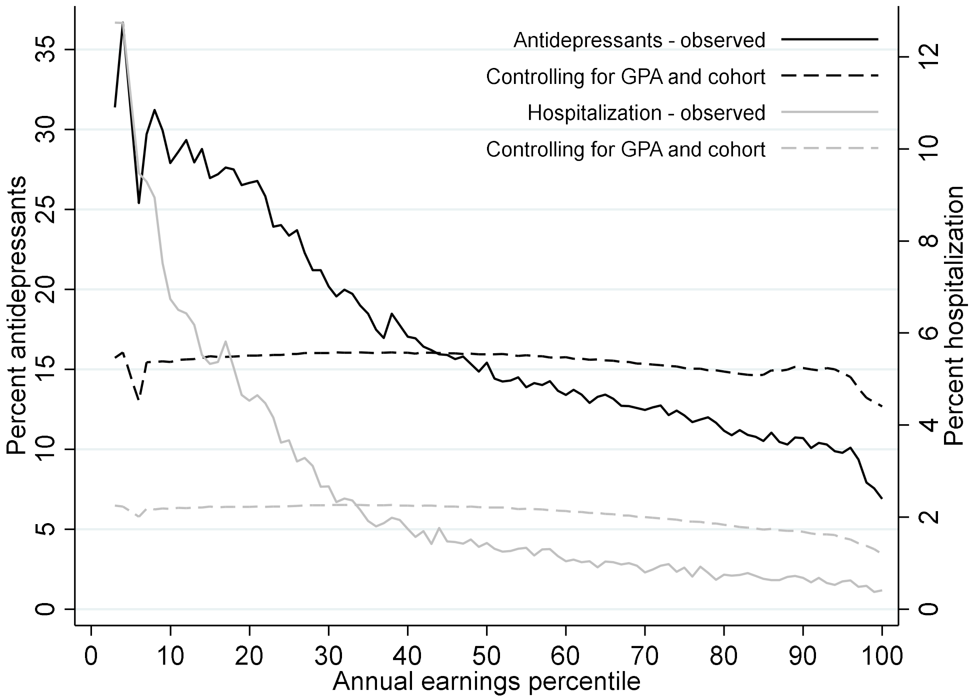
Notes: Total population incidence of hospitalizations due to mental disorders, averages across age based on observations from 1997 to 2019. The shaded area represents the age limits of the measure for our baseline analyses (age 36-44).

Figure 2. Incidence of antidepressants and hospitalizations due to mental disorders across ninth grade GPA.



Notes: Incidence of prescribed antidepressant medications at age 40-45 and incidence of hospitalizations due to mental disorders at age 36-44, against the unadjusted GPA of applicants 1977-1991. N = 1, 208,269.

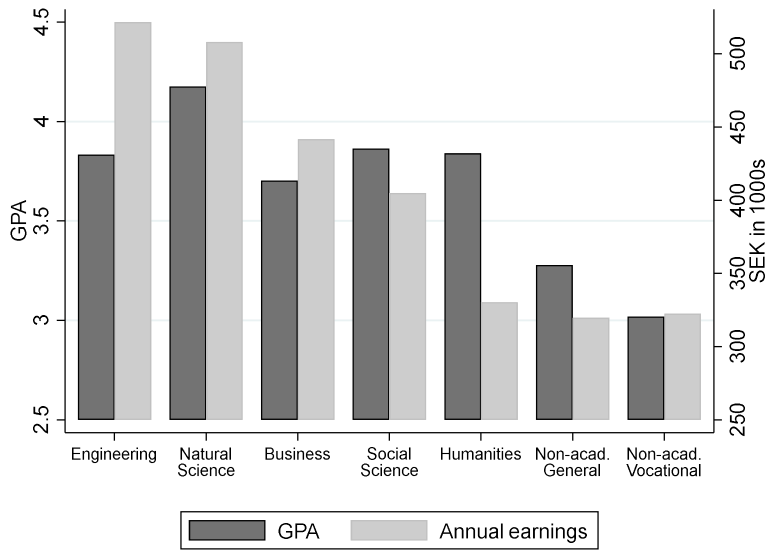
Figure 3. Incidence of antidepressants and hospitalization due to mental disorders across annual labor earnings percentiles in adult age.



Notes: Incidence of prescribed antidepressant medications at age 40-45 and incidence of hospitalizations due to mental disorders at age 36-44, against annual earnings rank based on mean earnings at age 41-43. Dashed lines are predicted values from a regression model controlling for GPA at age 16 and cohort fixed effects. Applicants to high school majors between 1977-1991. N=1,208,269.

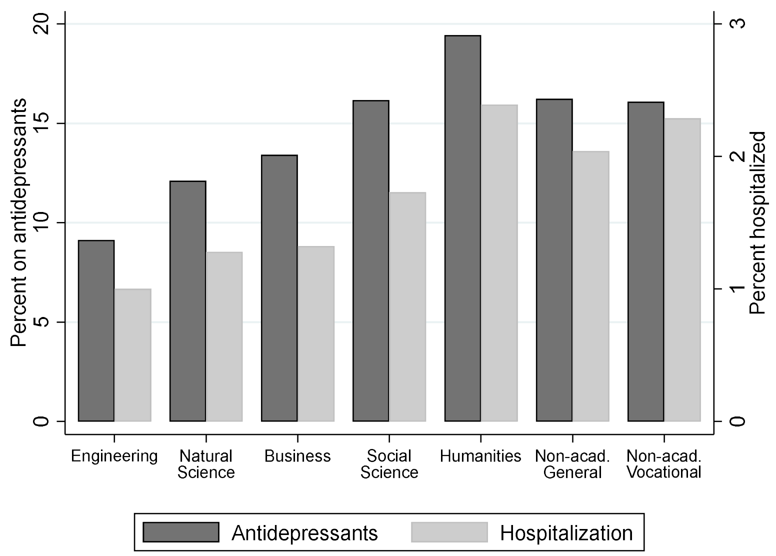
Figure 4. Program completers average GPA and adult outcomes.

Panel A: GPA (unadjusted) and adult annual earnings (right y-axis)



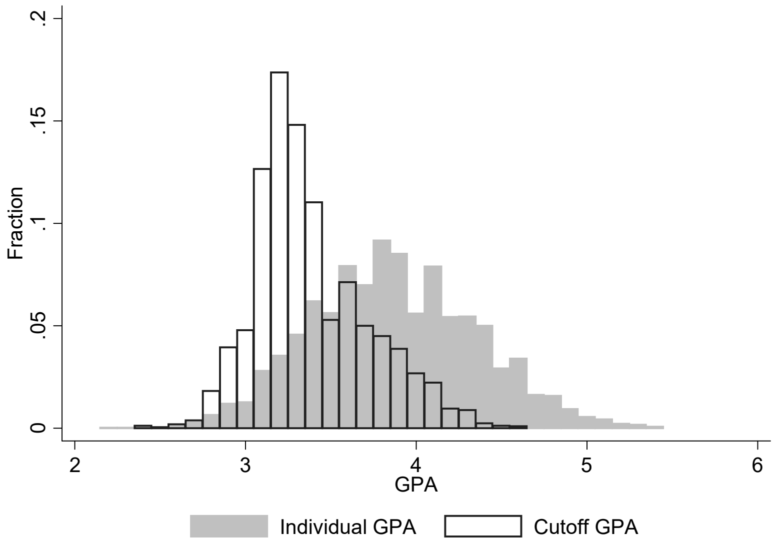
Notes: Sample of program completers who applied between 1977-1991. Adult earnings measured between the ages of 41-43. N =1,208,269 (N earnings = 1,148,133).

Panel B: Antidepressants and hospitalization (right y-axis)



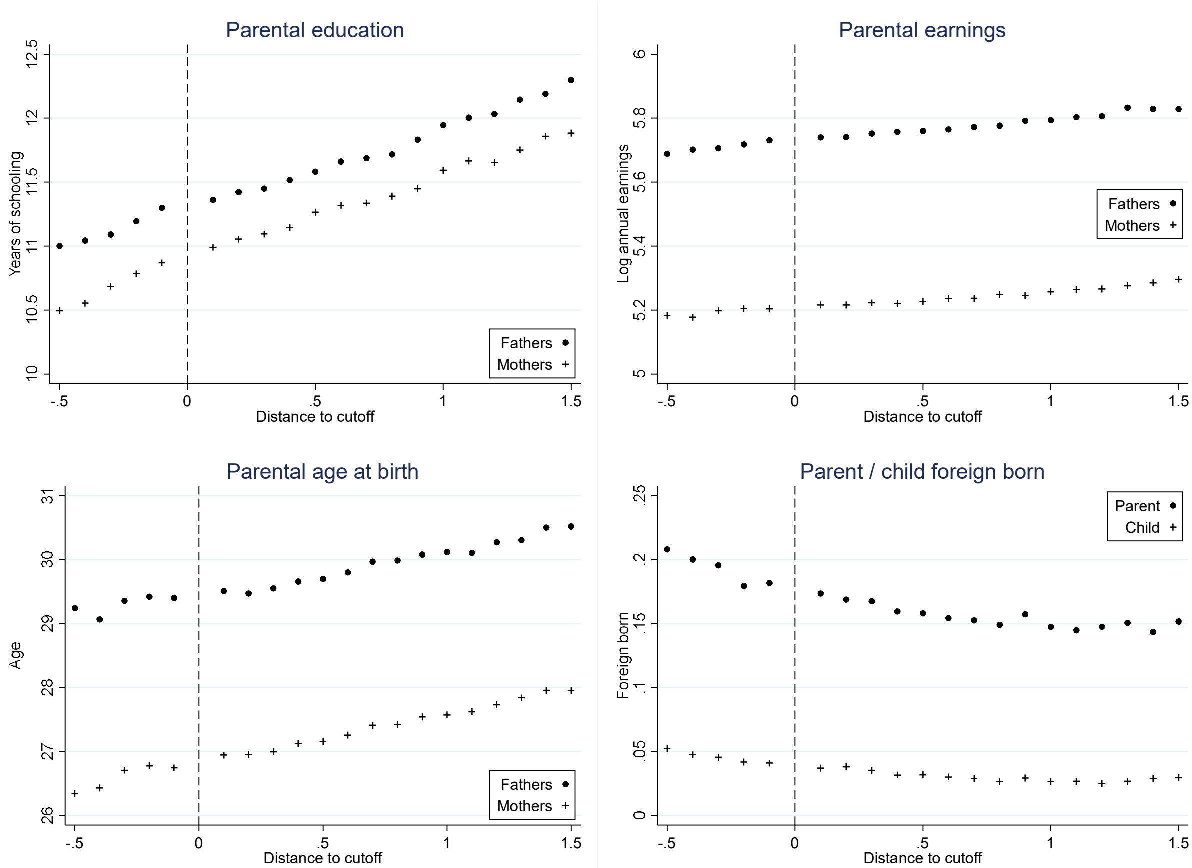
Notes: Sample of program completers who applied between 1977-1991. Incidence of prescribed antidepressants medications at age 40-45 and of hospitalizations due to mental disorders. N = 1,135,249,

Figure 5. Cutoff distribution versus individual GPA distribution.



Notes: The white bars plot the distribution of cutoff GPAs for oversubscribed programs, which vary by major, year, and school region. There are 3,487 oversubscribed programs in our estimation sample. The grey bars plot the distribution of GPA for individuals in our main analysis sample (N=247,074).

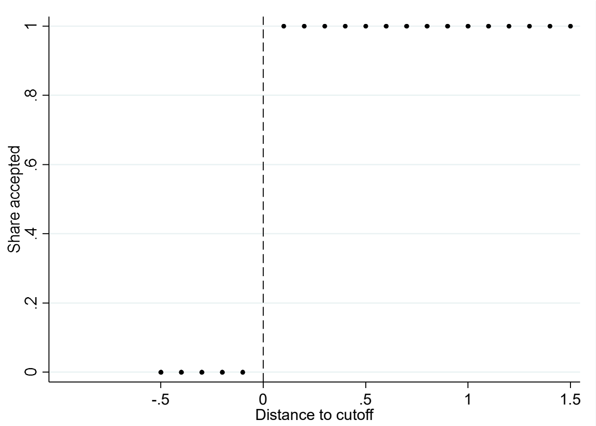
Figure 6. Smoothness of predetermined variables at the cutoff.



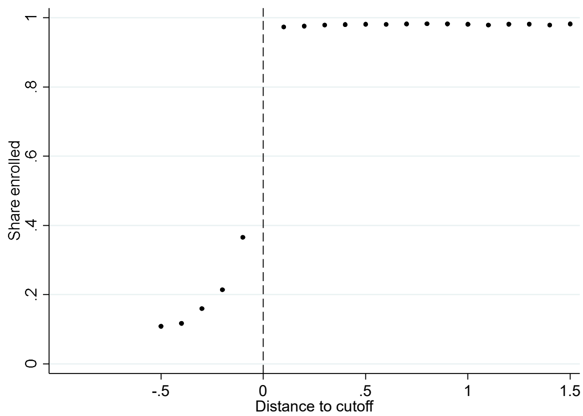
Notes: Each dot is the average for the relevant outcome in a .1 GPA bin. GPA is measured relative to a normalized cut-off of 0. Parent foreign born is a dummy for whether at least one parent is foreign born.

Figure 7. Discontinuity in admission (panel A) enrolment (B) and completion (C) as a function of GPA.

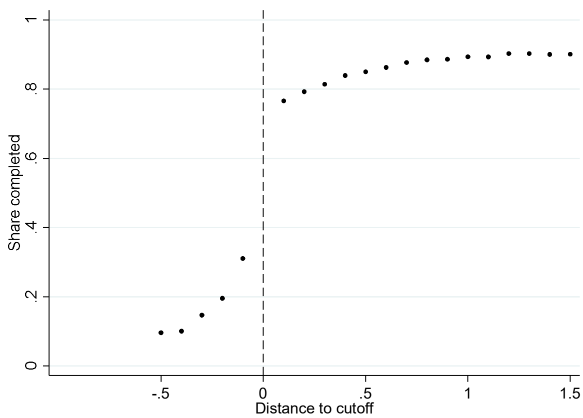
Panel A: Share admitted to their first choice



Panel B: Share enrolled in their first choice



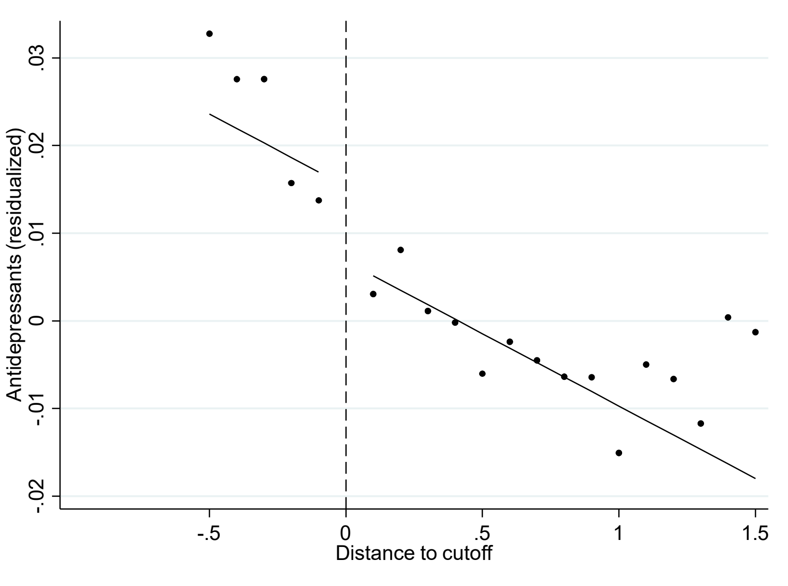
Panel C: Share completing their first choice



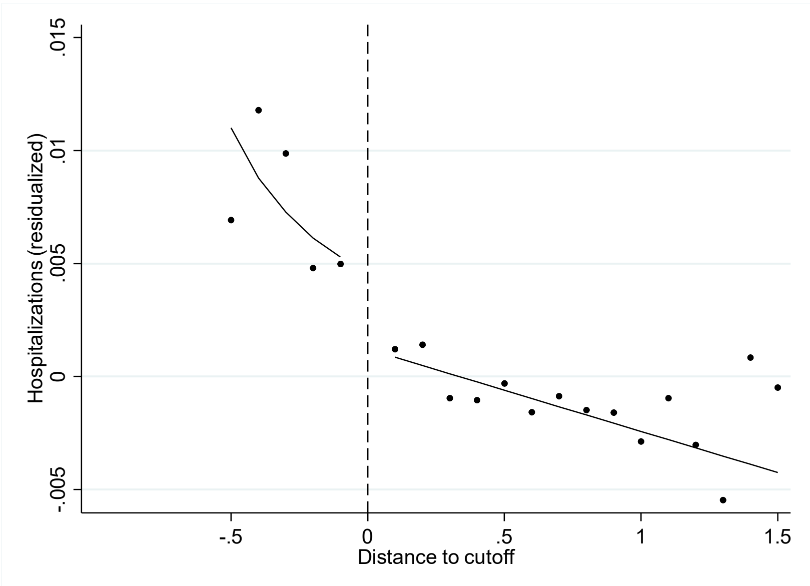
Notes: Each dot is the average acceptance rate, enrolment rate, or completion rate in a 0.1 GPA bin, where GPA is measured relative to a cutoff normalized to zero. N = 247,074.

Figure 8. Indicators of mental health in adult age by distance to cutoff , controlling for year and region fixed effects.

Panel A: Incidence of antidepressants at age 40-45

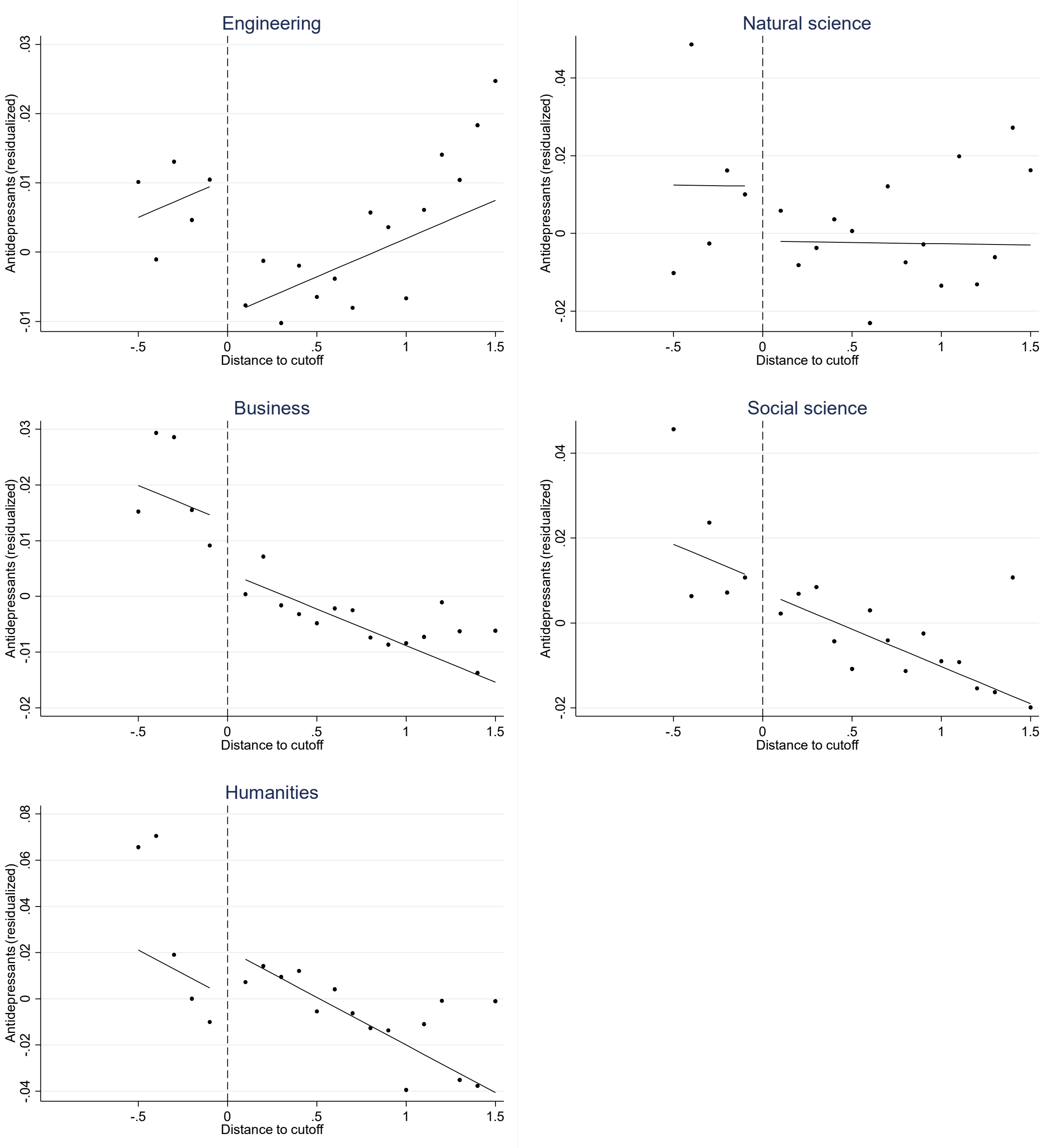


Panel B: Incidence of hospitalization at age 36-44



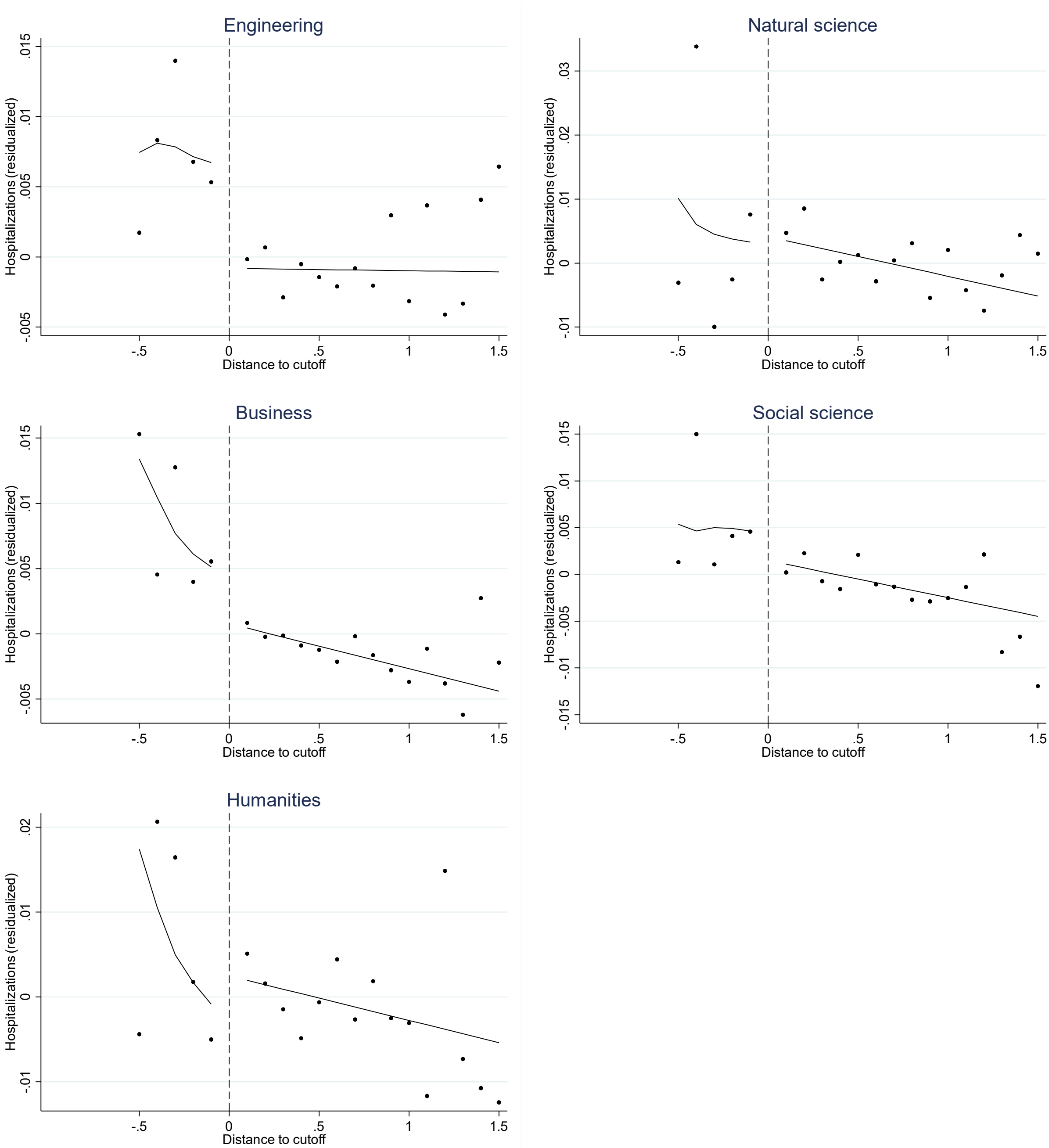
Notes: Each observation is the residualized average incidence (regressing out year and school-region fixed effects) of antidepressants at age 40-45 (panel A) or hospitalization due to mental illness (panel B) in a 0.1 GPA bin, where GPA is measured relative to a cutoff normalized to zero. The regression line is a linear function of GPA (antidepressants) adding squared terms to the left of the cutoff for each of the possible 7 second choices (hospitalization), estimated within a window of -0.5 to 1.5, applying triangular weights. The number of observations is 247,074.

Figure 9. Program specific incidence of antidepressants at age 40-45 by distance to cutoff, controlling for year and region fixed effects.



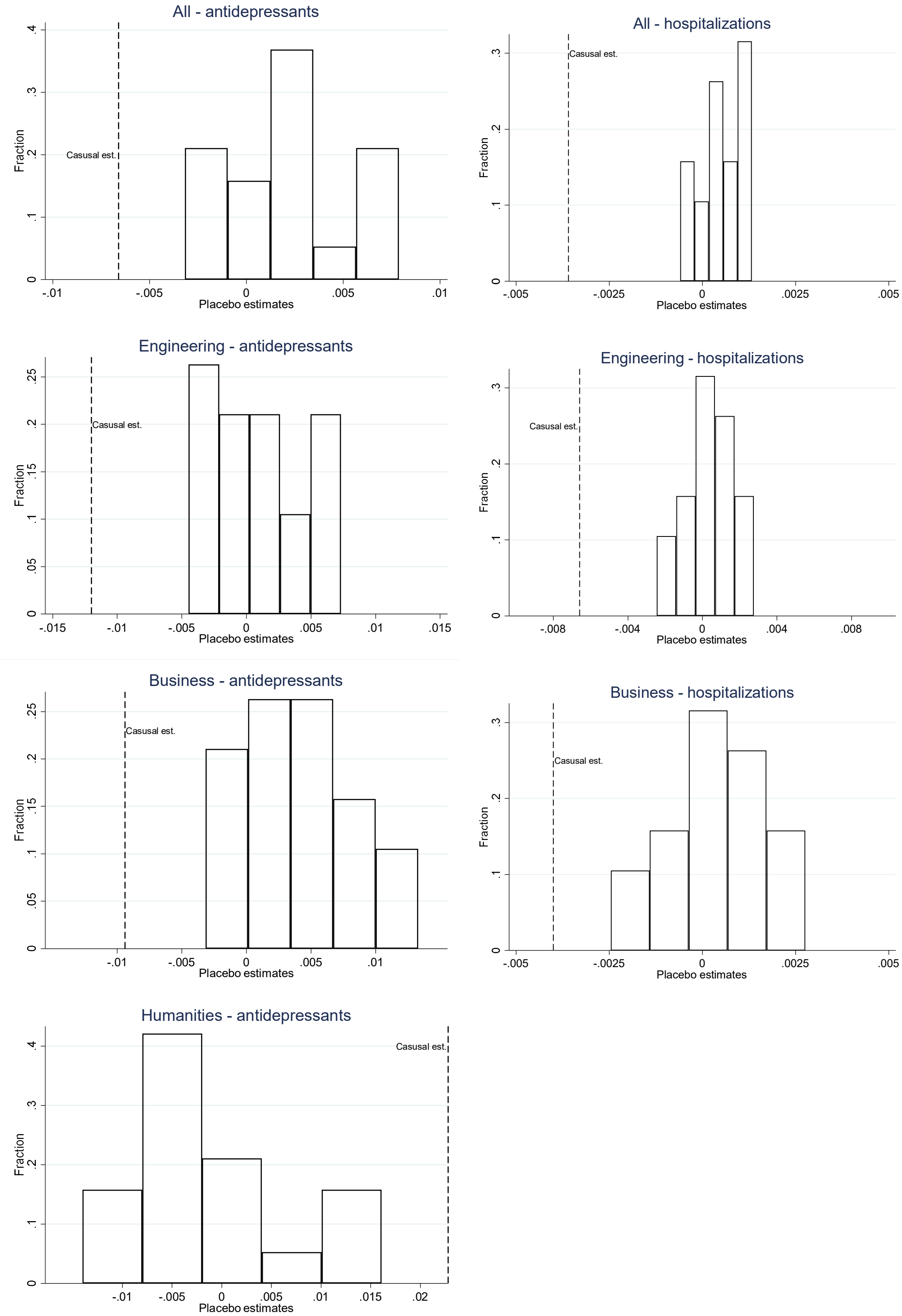
Notes: Each observation is the residualized average incidence (regressing out year and school-region fixed effects) of antidepressants at age 40-45 in a 0.1 GPA bin, where GPA is measured relative to a cutoff normalized to zero. The linear function of GPA is estimated within a window of -0.5 to 1.5, applying triangular weights. The number of observations is for engineering 68,998, for Natural science 21,339, for Business 93,300, for Social science 58,733 and for Humanities 16,642.

Figure 10. RD graphs for the program specific incidence of hospitalizations age 36-44 by distance to cutoff, controlling for year and region fixed effects.



Notes: Each observation is the residualized average incidence (regressing out year and school-region fixed effects) of hospitalization at age 36-44 in a 0.1 GPA bin, where GPA is measured relative to a cutoff normalized to zero. The regression lines are linear functions of GPA adding squared terms to the left of the cutoff for each of the possible 7 second choices, estimated within a window of -0.5 to 1.5, applying triangular weights. The number of observations is for engineering 68,998, for Natural science 21,339, for Business 93,300, for Social science 58,733 and for Humanities 16,642.

Figure 11. Randomization inference.



Notes: Distribution of placebo RD estimates using "fake" cutoffs. To avoid any jump at the true cutoff affecting these placebo estimates, the placebo windows all start after the true GPA cutoff. We impose a minimum of plus or minus three-tenths of a GPA point on each side of the fake cutoff. Dashed vertical lines denote the statistically significant estimates reported in Tables 4 and 5.

Table 1. Course requirements for each of the five academic programs.

	Weekly hours of course instruction				
Classes	Engineering	Natural Science	Business	Social Science	Humanities
Math	15^{adv}	15^{adv}	11	11	5
Natural science	17	22.5	3	9	7
Social science	11	16	16.5	25.5	25.5
Swedish	8	9	9	10	10
English	6	7	7	8	9
Additional languages	6	11	14	17	24
Art and music	-	4	-	4	4
Physical education	7	8	7	8	8
Technology related	22.5	-	-	-	-
Business related	-	-	25	-	-
Other	3.5	3.5	3.5	3.5	3.5
Total hours	96	96	96	96	96

Notes: The total amount of 96 hours consists of 34, 32, and 30 hours per week during the first, second, and third years, respectively. Engineering has an optional fourth year of 35 hours per week of mostly technology related courses. The superscript "adv" indicates that advanced math is required for Engineering and Natural Science. Business allows the possibility to exchange 3 hours of math with business-related courses. Natural science classes include physics, chemistry, and biology, while Social science classes include history, religion, philosophy, psychology, and social studies. These curricula are mandated by law and laid out in Lgy70 (Läroplan för gymnasieskolan); they remained unchanged during our sample period (1977-1991) but were modified in 1994.

Table 2. Oversubscribed and non-impacted program sample sizes and summary statistics for all applicants with a first-choice academic program 1977-1991.

	Baseline Sample:			
	Oversubscribed programs		Non-impacted programs	
First choice	Individuals	Programs	Individuals	Programs
Engineering	66,306	793	54,812	1,079
Natural Science	20,051	395	54,507	1,457
Business	89,194	1,030	38,180	815
Social Science	55,959	873	35,065	970
Humanities	15,564	396	26,869	1,467
Total	247,074	3,487	209,433	5,788
Woman	0.52		0.51	
Age when applying	16.00		15.99	
GPA	3.75		3.81	
GPA adjusted	3.87		3.93	
Foreign born	0.03		0.03	
Foreing born parent	0.16		0.16	
Father earnings	5.76		5.75	
Mother earnings	5.23		5.20	
Father schooling	11.61		11.29	
Mother schooling	11.24		10.81	
Father age	29.77		30.01	
Mother age	27.21		27.33	
Observations	247,074		209,433	

Notes: Programs are defined by major, year, and school region. "Individuals" refers to the number/share of students applying to either an oversubscribed or non-impacted program. Non-impacted programs do not have an excess supply of applicants, and so have unrestricted entry. Parent characteristics are measured in the year of application (the child's 16th year since birth).

Table 3. First stage estimates for the probability of enrolling or completing a first-choice major.

	Antidepressants		Hospitalizations	
Panel A – all:	Enrolled	Completed	Enrolled	Completed
All	.6912***	.4919***	.6390***	.4599***
	(.0030)	(.0035)	(.0037)	(.0041)
N	247,074	247,074	247,074	247,074
Panel B – by first choice program	Enrolled	Completed	Enrolled	Completed
Engineering	.6355***	.4092***	.5779***	.3740***
	(.0067)	(.0077)	(.0071)	(.0080)
Natural science	.5789***	.3976***	.5245***	.3665***
	(.0148)	(.0156)	(.0151)	(.0160)
Business	.7315***	.5584***	.6806***	.5269***
	(.0044)	(.0053)	(.0049)	(.0056)
Social science	.7103***	.5019***	.6584***	.4695***
	(.0057)	(.0069)	(.0063)	(.0073)
Humanities	.6634***	.4238***	.6136***	.3899***
	(.0109)	(.0133)	(.0111)	(.0134)
N	247,074	247,074	247,074	247,074

Notes: The outcome variable is a dummy for whether the individuals enrolled or completed their first-best major, as a function of whether their GPA exceeded the admissions cutoff. The regressions use a linear function of GPA (antidepressants) adding squared terms to the left of the cutoff for each of the possible 7 second choices (hospitalization), estimated within a window of -0.5 to 1.5, triangular weights, fixed effects for year and school region, dummies for preferred program as well as for next-best alternative program, and the demographic controls listed in Table 2. Standard errors in parentheses.

** p<0.10, ** p<0.05, *** p<0.01*

Table 4. Estimated impact of being admitted to the preferred field of study on the incidence of antidepressants when aged 40 to 45 and hospitalizations due to mental illness when aged 36 to 44.

	Reduced form	IV-enrolled	IV-completed	Mean
Panel A: Antidepressants 40-45				
Preferred field of study	-.0066**	-.0096**	-.0135**	[.1611]
	(.0031)	(.0044)	(.0062)	
N	247,074	247,074	247,074	
Panel B: Separate by 2nd choice				
- 2nd choice academic	-.0098**	-.0147**	-.0204**	[.1617]
	(.0042)	(.0063)	(.0087)	
- 2nd choice non-academic	-.0043	-.0061	-.0095	[.1605]
	(.0037)	(.0051)	(.0067)	
N	247,074	247,074	247,074	
Panel C: Hospitalization 36-44				
Preferred field of study	-.0036***	-.0056***	-.0077***	[.0193]
	(.0014)	(.0021)	(.0029)	
N	247,074	247,074	247,074	
Panel D: Separate by 2nd choice				
- 2nd choice academic	-.0060***	-.0097***	-.0134***	[.0196]
	(.0020)	(.0033)	(.0045)	
- 2nd choice non-academic	-.0018	-.0027	-.0044	[.0190]
	(.0017)	(.0025)	(.0033)	
N	247,074	247,074	247,074	

Notes: The outcome variables are the incidence of prescribed antidepressants (panel A and B) and the incidence of hospitalizations related to mental disorders (panel C and D). IV-enrolled uses as a first stage whether the individual enrolled in their first-best major, as a function of whether their GPA exceeded the admissions cutoff. IV-completed uses as first stage whether the individual completed their first-best major. The regressions use a linear function of GPA (antidepressants) adding squared terms to the left of the cutoff for each of the possible 7 second choices (hospitalization), estimated within a window of -0.5 to 1.5, triangular weights, fixed effects for year and school region, dummies for preferred program as well as for next-best alternative program, and the demographic controls listed in Table 2. The mean of the dependent variable is calculated for the sample where an individual's GPA is within plus or minus 0.2 GPA points of the admission cutoff. Standard errors in parentheses.
** p<0.10, ** p<0.05, *** p<0.01*

Table 5. Field of study impact on the incidence of antidepressants (panel A) and hospitalization (panel B). Reduced form and IV estimates.

	Reduced form	IV-enrolled	IV-completed	Mean
Panel A: Antidepressants				
Engineering	-.0120**	-.0189**	-.0287**	[.1050]
	(.0054)	(.0086)	(.0130)	
Natural science	-.0132	-.0227	-.0331	[.1562]
	(.0133)	(.0229)	(.0329)	
Business	-.0094*	-.0128*	-.0164*	[.1622]
	(.0049)	(.0067)	(.0087)	
Social science	-.0042	-.0059	-.0081	[.1897]
	(.0065)	(.0092)	(.0129)	
Humanities	.0228*	.0341*	.0523*	[.2257]
	(.0129)	(.0194)	(.0298)	
N	247,074	247,074	247,074	
Panel A: Hospitalizations				
Engineering	-.0066***	-.0110***	-.0166***	[.0143]
	(.0024)	(.0038)	(.0058)	
Natural science	.0023	.0035	.0052	[.0218]
	(.0052)	(.0090)	(.0129)	
Business	-.0040**	-.0059**	-.0075**	[.0182]
	(.0020)	(.0028)	(.0036)	
Social science	-.0028	-.0043	-.0060	[.0227]
	(.0027)	(.0038)	(.0054)	
Humanities	.0021	.0027	.0042	[.0277]
	(.0051)	(.0078)	(.0120)	
N	247,074	247,074	247,074	

Notes: The outcome variables are the incidence of prescribed antidepressants at age 40-45 (panel A) and the incidence of hospitalizations related to mental disorders at age 36-44 (panel B). IV-enrolled uses as a first stage whether the individual enrolled in their first-best major, as a function of whether their GPA exceeded the admissions cutoff. IV-completed uses as first stage whether the individual completed their first-best major. The regressions use a linear function of GPA (antidepressants) adding squared terms to the left of the cutoff for each of the possible 7 second choices (hospitalization), estimated within a window of -0.5 to 1.5, triangular weights, fixed effects for year and school region, dummies for preferred program as well as for next-best alternative program, and the demographic controls listed in Table 2. The mean of the dependent variable is calculated for the sample where an individual's GPA is within plus or minus 0.2 GPA points of the admission cutoff. Standard errors in parentheses.

** p<0.10, ** p<0.05, *** p<0.01*

Table 6. Incidence of antidepressants at age 40-45 by program and gender. Reduced form and IV estimates.

	Reduced form	IV-enrolled	IV-completed	Mean
Panel A – all:				
Women	-.0145***	-.0201***	-.0267***	[.2174]
	(.0047)	(.0065)	(.0087)	
Men	-.0010	-.0018	-.0046	[.1102]
	(.0033)	(.0048)	(.0065)	
N	247,074	247,074	247,074	
Panel B – by field of study				
Women				
Engineering	-.0211**	-.0344***	-.0598***	[.2227]
	(.0090)	(.0125)	(.0217)	
Natural science	-.0272*	-.0415*	-.0627*	[.2149]
	(.0149)	(.0243)	(.0373)	
Business	-.0202***	-.0273***	-.0343***	[.2098]
	(.0062)	(.0083)	(.0108)	
Social science	-.0129*	-.0169*	-.0207	[.2174]
	(.0071)	(.0099)	(.0136)	
Humanities	.0175	.0264	.0419	[.2446]
	(.0132)	(.0197)	(.0295)	
Men				
Engineering	-.0111**	-.0175**	-.0290**	[.0976]
	(.0055)	(.0086)	(.0135)	
Natural science	-.0076	-.0148	-.0256	[.1266]
	(.0133)	(.0228)	(.0319)	
Business	-.0003	-.0005	-.0035	[.1135]
	(.0052)	(.0070)	(.0088)	
Social science	.0111	.0144	.0150	[.1340]
	(.0073)	(.0102)	(.0138)	
Humanities	.0443***	.0613***	.1014***	[.1381]
	(.0155)	(.0214)	(.0367)	
N	247,074	247,074	247,074	

Notes: The outcome variable is the incidence of prescribed antidepressants at age 45-50. IV-enrolled uses as a first stage whether the individual enrolled in their first-best major, as a function of whether their GPA exceeded the admissions cutoff. IV-completed uses as first stage whether the individual completed their first-best major. The regression specifications follow the baseline model, linear functions of GPA, a window of -0.5 to 1.5, triangular weights, fixed effects for year and school region, dummies for preferred program as well as for next-best alternative program, and the demographic controls listed in Table 2. The mean of the dependent variable is calculated for the sample where an individual's GPA is within plus or minus 0.2 GPA points of the admission cutoff. Standard errors in parentheses.

** p<0.10, ** p<0.05, *** p<0.01*

Table 7. Incidence of hospitalization at age 36-44 by program and gender. Reduced form and IV estimates.

	Reduced form	IV-enrolled	IV-completed	Mean
Panel A – all:				
Women	-.0031*	-.0048*	-.0068*	[.0234]
	(.0019)	(.0027)	(.0036)	
Men	-.0039**	-.0062***	-.0084***	[.0157]
	(.0015)	(.0024)	(.0032)	
N	247,074	247,074	247,074	
Panel B – by field of study				
Women				
Engineering	-.0025	-.0067	-.0141	[.0310]
	(.0036)	(.0052)	(.0090)	
Natural science	.0052	.0064	.0098	[.0283]
	(.0057)	(.0095)	(.0146)	
Business	-.0051**	-.0070**	-.0089**	[.0206]
	(.0024)	(.0033)	(.0042)	
Social science	-.0031	-.0046	-.0063	[.0247]
	(.0029)	(.0040)	(.0056)	
Humanities	.0020	.0026	.0040	[.0271]
	(.0052)	(.0079)	(.0118)	
Men				
Engineering	-.0065***	-.0106***	-.0161***	[.0133]
	(.0024)	(.0038)	(.0060)	
Natural science	.0011	.0022	.0036	[.0185]
	(.0052)	(.0090)	(.0126)	
Business	-.0031	-.0048	-.0064*	[.0156]
	(.0022)	(.0031)	(.0038)	
Social science	-.0023	-.0037	-.0055	[.0187]
	(.0030)	(.0043)	(.0059)	
Humanities	.0028	.0037	.0058	[.0304]
	(.0064)	(.0088)	(.0152)	
N	247,074	247,074	247,074	

Notes: The outcome variable is the incidence of hospitalizations related to mental disorders at age 36-44. IV-enrolled uses as a first stage whether the individual enrolled in their first-best major, as a function of whether their GPA exceeded the admissions cutoff. IV-completed uses as first stage whether the individual completed their first-best major. The regression specifications follow the baseline model, linear functions of GPA adding squared terms to the left of the cutoff for each of the possible 7 second choices, estimated within a window of -0.5 to 1.5, triangular weights, fixed effects for year and school region, dummies for preferred program as well as for next-best alternative program, and the demographic controls listed in Table 2. The mean of the dependent variable is calculated for the sample where an individual's GPA is within plus or minus 0.2 GPA points of the admission cutoff. Standard errors in parentheses.

** p<0.10, ** p<0.05, *** p<0.01*

Table 8. Specification checks - reduced form estimates using alternative specifications.

	Baseline	No demo. controls	Smaller bandwidth	Excluding 1982-1984	Reverse baseline spec.	10 slope model	24 slope model	60 slope model	1st—2nd intercepts
Panel A: Antidepressants									
All	-.0066**	-.0071**	-.0032	-.0065*	-.0046	-.0061*	-.0025	-.0019	-.0068**
	(.0031)	(.0031)	(.0039)	(.0035)	(.0035)	(.0035)	(.0075)	(.0075)	(.0031)
N	247,074	247,074	188,625	207,583	247,074	247,074	247,074	247,074	247,074
Engineering	-.0120**	-.0125**	-.0125*	-.0123**	-.0083	-.0143**	-.0154	-.0135	-.0120**
	(.0054)	(.0054)	(.0070)	(.0061)	(.0057)	(.0064)	(.0103)	(.0103)	(.0055)
Natural sci.	-.0132	-.0133	-.0070	-.0076	-.0151	-.0135	-.0116	-.0089	-.0123
	(.0133)	(.0133)	(.0176)	(.0140)	(.0136)	(.0157)	(.0211)	(.0212)	(.0135)
Business	-.0094*	-.0098**	-.0040	-.0083	-.0077	-.0101*	-.0046	-.0040	-.0091*
	(.0049)	(.0049)	(.0062)	(.0055)	(.0051)	(.0055)	(.0091)	(.0092)	(.0049)
Social science	-.0042	-.0047	-.0012	-.0076	-.0025	-.0032	-.0011	-.0011	-.0053
	(.0065)	(.0065)	(.0084)	(.0073)	(.0068)	(.0073)	(.0113)	(.0113)	(.0066)
Humanities	.0228*	.0221*	.0273	.0286*	.0248*	.0349**	.0477**	.0455**	.0224*
	(.0129)	(.0129)	(.0169)	(.0150)	(.0130)	(.0143)	(.0190)	(.0191)	(.0132)
N	247,074	247,074	188,625	207,583	247,074	247,074	247,074	247,074	247,074
Panel B: Hospitalizations									
All	-.0036***	-.0036***	-.0026*	-.0040***	-.0042***	-.0036***	-.0037	-.0036	-.0035***
	(.0014)	(.0014)	(.0016)	(.0015)	(.0012)	(.0014)	(.0031)	(.0031)	(.0014)
N	247,074	247,074	188,625	207,583	247,074	247,074	247,074	247,074	247,074
Engineering	-.0066***	-.0067***	-.0056**	-.0076***	-.0076***	-.0071***	-.0070*	-.0067	-.0065***
	(.0024)	(.0024)	(.0028)	(.0027)	(.0022)	(.0026)	(.0042)	(.0043)	(.0024)
Natural sci.	.0023	.0023	.0040	.0040	.0017	.0029	.0010	.0000	.0032
	(.0052)	(.0052)	(.0069)	(.0054)	(.0050)	(.0060)	(.0086)	(.0086)	(.0051)
Business	-.0040**	-.0041**	-.0032	-.0045**	-.0048***	-.0041*	-.0039	-.0036	-.0038*
	(.0020)	(.0020)	(.0024)	(.0022)	(.0018)	(.0021)	(.0036)	(.0036)	(.0020)
Social science	-.0028	-.0029	-.0034	-.0040	-.0030	-.0036	-.0051	-.0050	-.0032
	(.0027)	(.0027)	(.0033)	(.0030)	(.0025)	(.0028)	(.0047)	(.0047)	(.0027)
Humanities	.0021	.0020	.0081	.0031	.0018	.0044	.0079	.0075	.0019
	(.0051)	(.0051)	(.0068)	(.0062)	(.0051)	(.0055)	(.0073)	(.0074)	(.0052)
N	247,074	247,074	188,625	207,583	247,074	247,074	247,074	247,074	247,074

Notes: See note to Table 5. Column 2 excludes the demographic controls listed in Table 2. Column 3 reduces the right-hand side bandwidth to half. Column 4 excludes the years 1982-84, when bonus GPA points were added for the first and second choices on an individual's ranking list. The next column 5 apply the baseline specifications reversed, so that the baseline specification for antidepressants is applied for hospitalization and vice versa. Column 6, 7 and 8 include a squared term to the left of the cutoff while expanding the number of linear slopes, with the 10-slope model referring to one slope for each of the 5 first choices and separately for men and women, the 24-slope model involves one slope for each of the 5 first choices, the 7 second choices, and separately for men and women, and the 60-slope model applies separate slopes to the left and right of the cutoff for each of the 30 possible first–second choice combination. Column 9 use first–second choice specific intercept terms. Standard errors in parentheses.
** p<0.10, ** p<0.05, *** p<0.01.*

Table 9. Mechanisms I - reduced form estimates of peer characteristics.

	GPA rank	Women share	College share
All	-.2327***	.0219***	.1405***
	(.0014)	(.0014)	(.0011)
N	247,074	247,074	247,074
Engineering	-.2852***	-.1035***	.1235***
	(.0035)	(.0036)	(.0029)
Natural sci.	-.1920***	.1184***	.3008***
	(.0067)	(.0079)	(.0044)
Business	-.2484***	.0266***	.0989***
	(.0021)	(.0019)	(.0016)
Social science	-.1760***	.0606***	.1885***
	(.0027)	(.0022)	(.0018)
Humanities	-.2048***	.1943***	.1389***
	(.0051)	(.0034)	(.0034)
N	247,074	247,074	247,074

Notes: See note to Table 6. The outcome in column 1 refers to the individual GPA rank among accepted students in year-region-program. Columns 2 and 3 refer to similarly calculated peer characteristics in terms of share of women (column 2) and share with a college degree (column 3). Standard errors in parentheses.
** p<0.10, ** p<0.05, *** p<0.01.*

Table 10. Mechanisms II - reduced form estimates using expected values of outcome variables.

	Baseline	Family situation	Earnings rank	Unemplyment incidence 33-43	Occupation	Workplace
Panel A: Antidepressants						
All	-.0066**	-.0008***	-.0026***	-.0021***	.0008*	.0002
	(.0031)	(.0003)	(.0006)	(.0004)	(.0004)	(.0005)
N	247,074	247,074	247,074	247,074	247,074	247,074
Engineering	-.0120**	-.0013**	-.0036***	-.0034***	-.0031***	-.0017
	(.0054)	(.0005)	(.0011)	(.0008)	(.0008)	(.0010)
Natural sci.	-.0132	-.0018	-.0034	-.0055***	.0022	-.0018
	(.0133)	(.0013)	(.0027)	(.0020)	(.0020)	(.0022)
Business	-.0094*	-.0006	-.0033***	-.0020***	.0021***	.0001
	(.0049)	(.0005)	(.0009)	(.0007)	(.0007)	(.0008)
Social science	-.0042	-.0008	-.0009	-.0016*	.0019**	.0020*
	(.0065)	(.0006)	(.0012)	(.0009)	(.0009)	(.0011)
Humanities	.0228*	.0009	-.0011	.0031*	.0017	.0018
	(.0129)	(.0012)	(.0025)	(.0017)	(.0017)	(.0021)
N	247,074	247,074	247,074	247,074	247,074	247,074
Panel B: Hospitalizations						
All	-.0036***	-.0004***	-.0012***	-.0004***	-.0006***	-.0001
	(.0014)	(.0002)	(.0003)	(.0001)	(.0002)	(.0002)
N	247,074	247,074	247,074	247,074	247,074	247,074
Engineering	-.0066***	-.0004	-.0012**	-.0007***	-.0008***	-.0002
	(.0024)	(.0003)	(.0006)	(.0003)	(.0003)	(.0004)
Natural sci.	.0023	-.0009	-.0015	-.0011*	-.0016***	-.0008
	(.0052)	(.0007)	(.0012)	(.0006)	(.0006)	(.0009)
Business	-.0040**	-.0003	-.0016***	-.0005**	-.0007***	-.0002
	(.0020)	(.0002)	(.0004)	(.0002)	(.0002)	(.0003)
Social science	-.0028	-.0008**	-.0008	-.0005	-.0003	.0002
	(.0027)	(.0003)	(.0005)	(.0003)	(.0003)	(.0004)
Humanities	.0021	.0003	-.0005	.0011**	-.0002	.0002
	(.0051)	(.0006)	(.0010)	(.0005)	(.0005)	(.0008)
N	247,074	247,074	247,074	247,074	247,074	247,074
Antidepressant						
Mean	.1526	.1851	.1573	.1645	.1576	.1614
St. dev.	.3596	.0717	.0717	.0542	.0620	.1606
Hospitalization						
Mean	.0102	.0284	.0197	.0222	.0182	.0200
St. dev.	.1004		.0271	.0140	.0145	.0557

Notes: See note to Table 5. Column 2 applies the expected value of antidepressants / hospitalizations defined as population cohort specific leave-out-means by gender for married/unmarried, with 0, 1, 2 or more than three children, in total 16 categories for each cohort. Column 3 applies population cohort specific leave-out-means for 200 earnings rank (half) percentiles categories. Column 4 applies population cohort specific leave-out-means for the frequency of the yearly unemployment incidence between age 33 and 43. Column 5 applies population cohort specific leave-out-means for 327 occupation categories and column 6 applies population cohort specific leave-out-means for 19,594 workplaces with at least ten employees. See text for further details. Standard errors in parentheses.
** p<0.10, ** p<0.05, *** p<0.01.*

Appendix
for Online Publication

"Field of Study and Long-Term Mental Health"

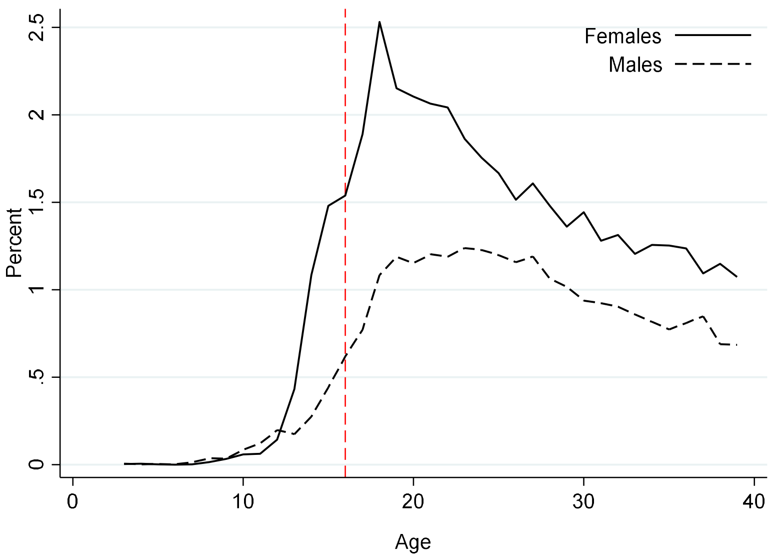
Anders Stenberg and Simona Tudor

Definition of the incidence of hospitalization due to mental disorders.

We restrict our definition of hospitalizations for mental disorders to International Classification of Diseases 10th Revision (ICD10) codes linked to environmental and lifestyle/socioeconomic factors rather than to biological factors. Specifically, in the definition of our hospitalizations for mental disorders we include individuals with one of the following ICD10 diagnostic codes (individuals often receive more than one diagnosis): F10–F19 mental and behavioral disorders due to psychoactive substance use; F30–F39 mood [affective] disorders; F40–F48 neurotic, stress-related and somatoform disorders; F50–F59 behavioral syndromes associated with physiological disturbances and physical factors. We exclude F00–F09 organic, including symptomatic, mental disorders; F20–F29 schizophrenia, schizotypal and delusional disorders; F60–F69 disorders of adult personality and behavior; F70–F79 mental retardation; F80–F89 disorders of psychological development; F90–F98 behavioral and emotional disorders with onset usually occurring in childhood and adolescence; F99–F99 unspecified mental disorders.

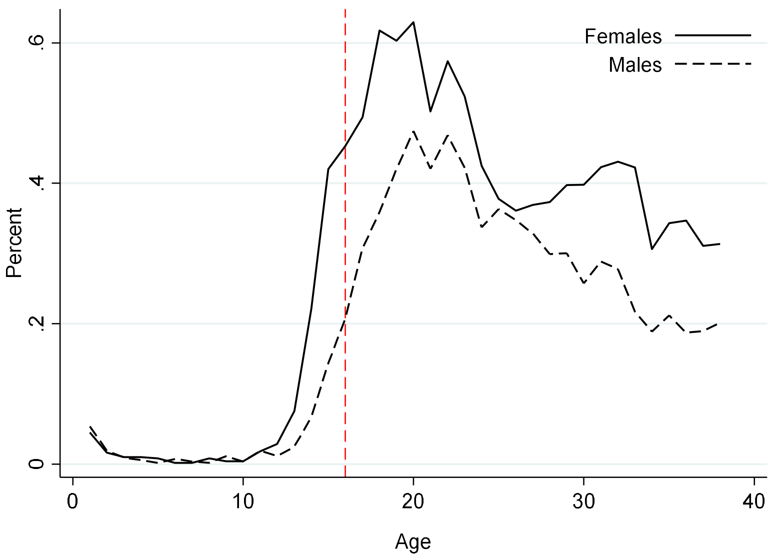
Figure A1. Total population first-time incidence of antidepressants and hospitalizations due to mental disorders.

Panel A: Incidence of antidepressants



Notes: Total population first-time incidence of prescribed antidepressant medications across age based on observations 2005 to 2019. Vertical line at age 16, the timing of high-school start. Incidence until age 14 is based on cohort born 2005, incidence age 15 on cohort born 2004 observed in 2019 conditioned on no incidence age 1-14, age 16 on cohort born 2003 observed in 2019 conditioned on no incidence age 2-15, and so forth, until age 39 based cohort born 1980 observed in 2019 conditioned on no incidence age 25-38.

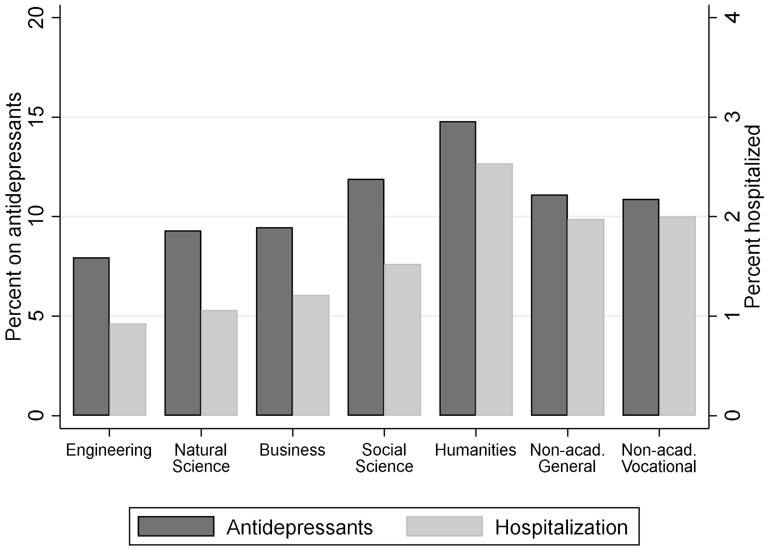
Panel B: Incidence of hospitalization due to mental disorders



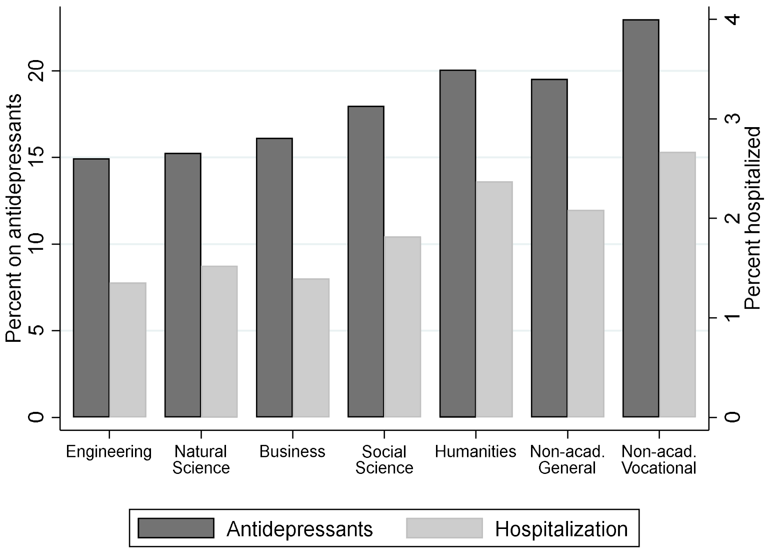
Notes: Total population first-time incidence of hospitalization due to mental disorders across age based on observations 1997 to 2018. Vertical line at age 16, the timing of high-school start. Incidence until age 21 is based on cohort born 1997, age 22 on cohort born 1996 and observed in 2018 conditioned on no incidence age 1-21, age 23 on cohort born 1995 and observed in 2018 conditioned on no incidence age 2-22, and so forth, until age 39 based cohort born 1979 and observed in 2018 conditioned on no incidence age 18-38.

Figure A2. Program completers and adult outcomes.

Panel A: Men - antidepressants and hospitalization (right y-axis)

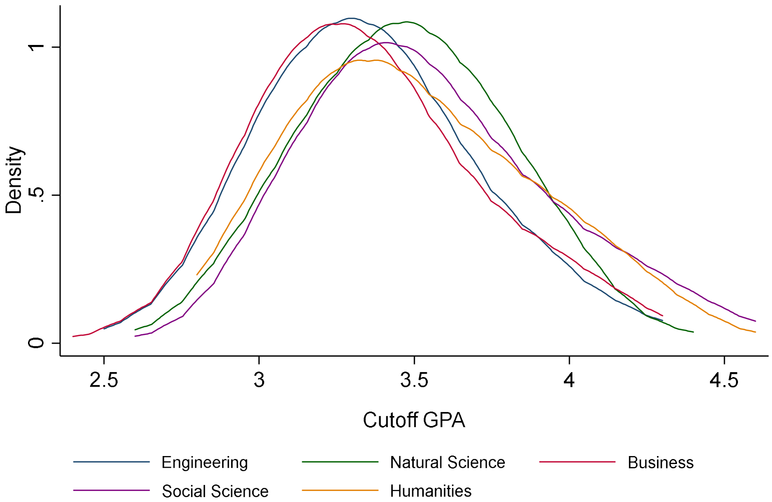


Panel B: Women - antidepressants and hospitalization (right y-axis)



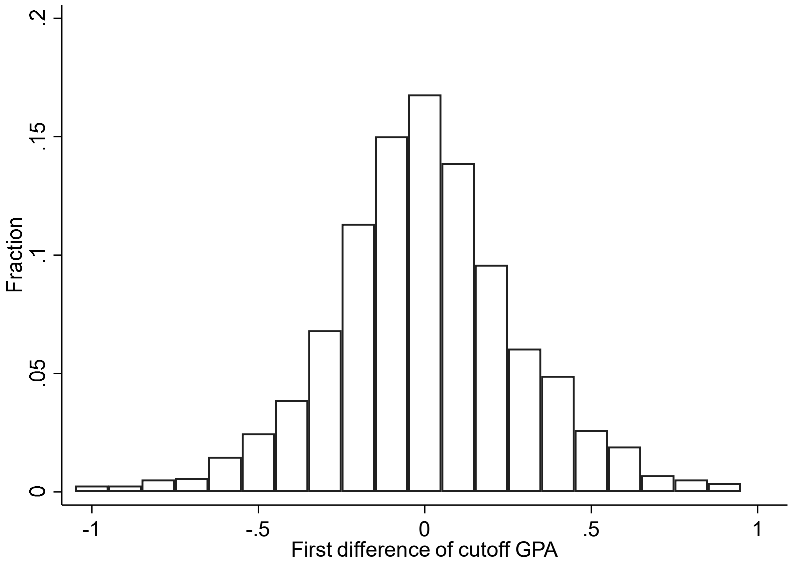
Notes: Sample of program completers who applied between 1977-1991. Incidence of prescribed antidepressants medications at age 40-45 and of hospitalizations due to mental disorders. N_{men}= 553,824; N_{women} = 581,425,

Figure A3. Distribution of GPA cutoffs by high school major



Notes: Kernel density estimates of GPA cutoffs by major for oversubscribed programs, applying an Epanechnikov kernel with bandwidth 0.2.

Figure A4. First-differenced cutoff GPA distribution



Notes: Current minus lagged cutoff GPA, where the sample is limited to majors which are competitive two years in a row in a school region.

Table A1. Program specific summary statistics of main analysis sample.

	First choice:				
	Engineering	Natural science	Business	Social science	Humanities
Women	0.17	0.49	0.60	0.72	0.86
Age when applying	16.00	15.98	16.00	15.99	15.99
GPA	3.75	4.04	3.65	3.80	3.76
GPA adjusted	3.88	4.11	3.75	3.94	3.90
Foreign born	0.03	0.04	0.03	0.03	0.05
Foreing born parent	0.16	0.17	0.16	0.16	0.21
Father earnings	5.76	5.86	5.74	5.77	5.72
Mother earnings	5.22	5.31	5.21	5.26	5.23
Father schooling	11.57	12.78	11.20	11.90	11.48
Mother schooling	11.17	12.34	10.83	11.63	11.12
Father age	29.71	29.84	29.69	29.89	29.99
Mother age	27.15	27.46	27.11	27.34	27.30
2nd choice					
Engineering	--	0.47	0.09	0.03	0.03
Natural science	0.50	--	0.08	0.16	0.04
Business	0.19	0.12	--	0.30	0.17
Social science	0.05	0.30	0.35	--	0.52
Humanities	0.01	0.04	0.10	0.30	--
Non-ac. General	0.07	0.02	0.22	0.15	0.16
Non-ac. Vocational	0.17	0.05	0.16	0.06	0.09
Observations	66,306	20,051	89,194	55,959	15,564

Notes: Oversubscribed programs are defined by major, year, and school region. Parent characteristics are measured in the year of application (the child's 16th year since birth).

Table A2. Comparison of major cutoffs across years within the same school region.

Major combinations	Fraction of years with a higher cutoff		
	1st major	2nd major	No difference
Engineering vs. Natural Science	.37	.25	.38
Engineering vs. Business	.28	.42	.30
Engineering vs. Social Science	.21	.53	.27
Engineering vs. Humanities	.31	.38	.31
Natural Science vs. Business	.24	.46	.30
Natural Science vs. Social Science	.18	.51	.31
Natural Science vs. Humanities	.24	.38	.39
Business vs. Social Science	.24	.48	.28
Business vs. Humanities	.37	.32	.31
Social Science vs. Humanities	.47	.21	.32

Notes: The table reports the average fraction of years with a higher cutoff for one major compared to another within the same school region. If both majors have a cutoff in a given year in the same school region, we compare the two to determine which is higher. If one major has a cutoff, but the other does not, we record the major with the cutoff as having a higher cutoff. "No difference" can either reflect that both majors have cutoffs which are equal or that neither major was oversubscribed.

Table A3. Balancing tests for pre-determined characteristics.

	Years of schooling father	Years of schooling mother	Log earnings father	Log earnings mother	Age at birth father	Age at birth mother	Foreign born parent	Child foreign born
	-.0511	-.0278	-.0045	-.0047	-.0908	-.0354	.0010	.0004
	(.0313)	(.0286)	(.0052)	(.0045)	(.0725)	(.0621)	(.0046)	(.0024)
N	234,050	243,120	201,514	184,914	233,845	242,653	247,068	247,074

Notes: Each column is an estimate from a separate RD regression, where the outcome is a linear function of the running variable (normalized GPA) within a window of -0.5 to 1.5, using triangular weights; fixed effects for year, school region, and program, and a common slope on each side of the cutoff. Standard errors in parentheses.
** p<.10, ** p<.05, *** p<.01*

Table A4. Field of study impact on the incidence of antidepressants (panel A) and hospitalization (panel B). Reduced form and IV estimates separately by second choice academic or non-academic.

	Reduced form	IV-enrolled	IV-completed	Mean
Panel A: Antidepressants				
Engineering – acadmic 2nd	-.0124**	-.0214**	-.0324**	[.1081]
	(.0063)	(.0097)	(.0142)	
- non-academic 2nd	-.0127**	-.0184**	-.0287**	[.1009]
	(.0060)	(.0091)	(.0137)	
Natural science – acadmic 2nd	-.0163	-.0252	-.0379	[.1583]
	(.0135)	(.0230)	(.0329)	
- non-academic 2nd	-.0004	-.0056	-.0164	[.1459]
	(.0177)	(.0287)	(.0492)	
Business – acadmic 2nd	-.0159**	-.0221**	-.0276**	[.1576]
	(.0063)	(.0088)	(.0111)	
- non-academic 2nd	-.0067	-.0094	-.0132	[.1658]
	(.0052)	(.0069)	(.0090)	
Social science – acadmic 2nd	-.0066	-.0099	-.0134	[.1883]
	(.0071)	(.0099)	(.0137)	
- non-academic 2nd	-.0013	-.0011	-.0027	[.1928]
	(.0078)	(.0106)	(.0148)	
Humanities – acadmic 2nd	.0166	.0262	.0405	[.2270]
	(.0136)	(.0200)	(.0293)	
- non-academic 2nd	.0302**	.0446**	.0814**	[.2237]
	(.0148)	(.0214)	(.0391)	
N	247,074	247,074	247,074	
Panel A: Hospitalizations				
Engineering – acadmic 2nd	-.0094***	-.0156***	-.0229***	[.0138]
	(.0028)	(.0047)	(.0068)	
- non-academic 2nd	-.0043	-.0073*	-.0123**	[.0151]
	(.0026)	(.0041)	(.0061)	
Natural science – acadmic 2nd	.0002	.0006	.0003	[.0215]
	(.0053)	(.0091)	(.0131)	
- non-academic 2nd	.0074	.0117	.0190	[.0235]
	(.0068)	(.0112)	(.0191)	
Business – acadmic 2nd	-.0075***	-.0116***	-.0144***	[.0179]
	(.0027)	(.0041)	(.0051)	
- non-academic 2nd	-.0024	-.0034	-.0049	[.0183]
	(.0021)	(.0030)	(.0038)	
Social science – acadmic 2nd	-.0046	-.0077*	-.0104*	[.0234]
	(.0030)	(.0044)	(.0061)	
- non-academic 2nd	-.0010	-.0009	-.0021	[.0213]
	(.0032)	(.0045)	(.0062)	
Humanities – acadmic 2nd	-.0004	-.0018	-.0019	[.0264]
	(.0055)	(.0081)	(.0119)	
- non-academic 2nd	.0039	.0060	.0108	[.0296]
	(.0059)	(.0087)	(.0159)	
N	247,074	247,074	247,074	

Notes: See note to Table 5 and text for details. The outcome variables are the incidence of prescribed antidepressants at age 40-45 (panel A) and the incidence of hospitalizations related to mental disorders at age 36-44 (panel B). IV-enrolled uses as a first stage whether the individual enrolled in their first-best major, as a function of whether their GPA exceeded the admissions cutoff. IV-completed uses as first stage whether the individual completed their first-best major. Standard errors in parentheses.
** p<0.10, ** p<0.05, *** p<0.01*

Table A5. Estimates for separate for each combination of first and second choices.

	Antidepressants	Hospitalizations	% with 2nd choice	Earnings 37-39
Eng vs. Nat sci	-.0179**	-.0110***	50	.065***
	(.0079)	(.0041)		(.017)
Eng vs. Bus	-.0161*	-.0100**	19	.007
	(.0095)	(.0045)		(.018)
Eng vs. Soc sci	.0002	-.0065	5	.059**
	(.0123)	(.0059)		(.025)
Eng vs. Hum	-.0052	-.0012	1	.070*
	(.0202)	(.0096)		(.039)
Eng vs. Gen non-ac	-.0062	-.0035	7	.010
	(.0082)	(.0036)		(.017)
Eng vs. Voc non-ac	-.0098	-.0036	17	.020
	(.0068)	(.0030)		(.015)
Nat sci vs. Eng	.0003	.0029	47	.039
	(.0150)	(.0060)		(.025)
Nat sci vs. Bus	-.0359**	.0013	12	.056**
	(.0172)	(.0074)		(.028)
Nat sci vs. Soc sci	-.0268	-.0011	30	.075***
	(.0168)	(.0072)		(.028)
Nat sci vs. Hum	-.0145	.0021	4	.060
	(.0235)	(.0097)		(.037)
Nat sci vs. Gen non-ac	-.0216	-.0078	2	.031
	(.0241)	(.0062)		(.052)
Nat sci vs. Voc non-ac	-.0016	.0134	5	-.032
	(.0206)	(.0087)		(.040)
Bus vs. Eng	.0033	-.0015	9	.046**
	(.0114)	(.0051)		(.021)
Bus vs. Nat sci	-.0297***	-.0083*	8	.091***
	(.0098)	(.0049)		(.017)
Bus vs. Soc sci	-.0165*	-.0081	35	.053***
	(.0097)	(.0050)		(.016)
Bus vs. Hum	-.0116	-.0086*	10	-.008
	(.0112)	(.0051)		(.018)
Bus vs. Gen non-ac	-.0073	-.0020	22	-.011
	(.0060)	(.0025)		(.010)
Bus vs. Voc non-ac	-.0080	-.0032	16	-.016
	(.0070)	(.0030)		(.011)
Soc sci vs. Eng	.0158	.0026	3	-.072***
	(.0155)	(.0065)		(.026)
Soc sci vs. Nat sci	-.0292***	-.0099*	16	.016
	(.0108)	(.0051)		(.018)
Soc sci vs. Bus	-.0043	-.0041	30	-.066***
	(.0094)	(.0044)		(.014)
Soc sci vs. Hum	-.0070	-.0046	30	-.030*
	(.0103)	(.0048)		(.017)
Soc sci vs. Gen non-ac	-.0021	-.0027	15	-.073***
	(.0087)	(.0035)		(.013)
Soc sci vs. Voc non-ac	-.0046	.0022	6	-.094***
	(.0113)	(.0047)		(.016)
Hum vs. Eng	.0218	-.0042	3	.033
	(.0270)	(.0095)		(.140)
Hum vs. Nat sci	-.0040	-.0082	4	-.025
	(.0247)	(.0094)		(.039)
Hum vs. Bus	.0188	.0008	17	-.124***
	(.0168)	(.0069)		(.021)
Hum vs. Soc sci	.0183	-.0006	52	-.046**
	(.0156)	(.0069)		(.021)
Hum vs. Gen non-ac	.0142	.0038	16	-.100***
	(.0161)	(.0066)		(.028)
Hum vs. Voc non-ac	.0559***	.0032	9	-.111***
	(.0199)	(.0076)		(.031)
N	247,074	247,074		233,034

Notes: See notes to Table 5 and text for details. Earnings estimates from Dahl et al. (2023). Standard errors in parentheses.

Table A6. Incidence of antidepressamts at age 45-50 (panel A) and at age 44-45 (panel B) by program. Reduced form and IV estimates.

	Reduced form	IV-enrolled	IV-completed	Mean
Panel A – incidence age 45-50:				
All	-.0065*	-.0094*	-.0133*	[.2023]
	(.0034)	(.0049)	(.0068)	
	247,074	247,074	247,074	
Engineering	-.0144**	-.0226**	-.0343**	[.1405]
	(.0062)	(.0097)	(.0147)	
Natural science	-.0166	-.0286	-.0414	[.1887]
	(.0144)	(.0248)	(.0356)	
Business	-.0103*	-.0140*	-.0179*	[.2039]
	(.0054)	(.0073)	(.0095)	
Social science	.0007	.0010	.0016	[.2319]
	(.0070)	(.0099)	(.0139)	
Humanities	.0219	.0328	.0504	[.2830]
	(.0140)	(.0209)	(.0322)	
N	247,074	247,074	247,074	
Panel B – incidence age 44 or 45				
All	-.0047*	-.0068*	-.0096*	[.1164]
	(.0025)	(.0036)	(.0051)	
N	247,074	247,074	247,074	
Engineering	-.0084*	-.0132**	-.0201**	[.0737]
	(.0043)	(.0067)	(.0102)	
Natural science	-.0012	-.0021	-.0033	[.1110]
	(.0106)	(.0182)	(.0262)	
Business	-.0057	-.0078	-.0099	[.1166]
	(.0040)	(.0054)	(.0071)	
Social science	-.0070	-.0099	-.0137	[.1336]
	(.0054)	(.0076)	(.0108)	
Humanities	.0183*	.0274*	.0419*	[.1743]
	(.0109)	(.0164)	(.0253)	
N	247,074	247,074	247,074	

Notes: See notes to table 6. The outcome variable is the incidence of prescribed antidepressants at age 45-50 or at age 44-45. For the age windows 40–45 and 45–50, data need to be slightly adjusted for the youngest or the oldest cohorts. Using antidepressants at age 40–45 as outcome, we apply for the oldest cohorts age 41–46 if born in 1964, age 42–47 for the cohort born in 1963, age 43–48 for the cohort born in 1962, and age 44–49 for the cohort born in 1961. Conversely, when we use age 45–50 we instead need to adjust the outcome of the youngest cohorts, age 44–49 for the cohort born in 1971, 43–48 for the cohort born in 1972, 42–47 for the cohort born in 1973, 41–46 for the cohort born in 1974 and 40–45 for the cohort born in 1975. The mean of the dependent variable is calculated for the sample where an individual's GPA is within plus or minus 0.2 GPA points of the admission cutoff. Standard errors in parentheses.

** p<0.10, ** p<0.05, *** p<0.01*

Table A7. Incidence of hospitalization at age 36-40 (panel A) and at age 40-44 (panel B) by program. Reduced form and IV estimates.

	Reduced form	IV-enrolled	IV-completed	Mean
Panel A – incidence age 36-40:				
All	-.0019*	-.0029*	-.0040*	[.0114]
	(.0011)	(.0016)	(.0023)	
N	247,074	247,074	247,074	
Engineering	-.0037**	-.0061**	-.0092**	[.0076]
	(.0018)	(.0029)	(.0044)	
Natural science	-.0002	-.0007	-.0009	[.0143]
	(.0043)	(.0076)	(.0109)	
Business	-.0032**	-.0046**	-.0058**	[.0105]
	(.0015)	(.0021)	(.0028)	
Social science	-.0006	-.0010	-.0013	[.0139]
	(.0021)	(.0030)	(.0042)	
Humanities	.0062	.0092	.0141	[.0176]
	(.0041)	(.0063)	(.0097)	
N	247,074	247,074	247,074	
Panel B – incidence age 40-44:				
All	-.0032***	-.0050***	-.0069***	[.0129]
	(.0011)	(.0017)	(.0024)	
	247,074	247,074	247,074	
Engineering	-.0056***	-.0094***	-.0142***	[.0104]
	(.0020)	(.0033)	(.0049)	
Natural science	.0026	.0041	.0059	[.0143]
	(.0040)	(.0070)	(.0101)	
Business	-.0031*	-.0046**	-.0059**	[.0124]
	(.0016)	(.0023)	(.0030)	
Social science	-.0023	-.0035	-.0049	[.0145]
	(.0021)	(.0031)	(.0044)	
Humanities	-.0029	-.0047	-.0072	[.0176]
	(.0041)	(.0063)	(.0097)	
N	247,074	247,074	247,074	

Notes: See notes to table 7. The outcome variable is the incidence of hospitalizations related to mental disorders at age 36-40 (panel A) and age 40-44 (panel B). IV-enrolled uses as a first stage whether the individual enrolled in their first-best major, as a function of whether their GPA exceeded the admissions cutoff. IV-completed uses as first stage whether the individual completed their first-best major. The mean of the dependent variable is calculated for the sample where an individual's GPA is within plus or minus 0.2 GPA points of the admission cutoff. Standard errors in parentheses.

** p<0.10, ** p<0.05, *** p<0.01*